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The Effects Of Individual-Level Income And Contextual-Level Income Inequality On Health

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by

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DEDICATION

“Education is not the filling of a pail, but the lighting of a fire.”
William Butler Yeats

To everyone who helped me start the fire
and keep it burning, I say “Thank You”.
I am truly blessed.

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CHAPTER 1: INTRODUCTION

Since the 1970's, income inequality in the US has been on the rise but has accelerated precipitously since the beginning of the Great Recession in 2008 (Keister 2014). While all demographic groups experienced drops in income, the declines have been greater for some groups than others (Pfeffer etal 2013; Grusky, et al 2011). The economic recovery since then has increased the income only of the richest 1% in the income distribution and generated no increases for the bottom 99% (Piketty and Saez 2003, updated 2013). Concomitant with the rise in income inequality has been a widening of differences in the effects of poor health for older individuals with high and low income status (Bosworth, Burtless, and Zhang 2014). Understanding the link between income inequality and health is salient, given that recent trends suggest that growing income inequality shows no sign of slowing down (Piketty and Saez 2003, updated 2013). Individuals living in the U.S. live in extraordinarily unequal worlds, where some have the resources to better their health and others do not.

There have been two strands of thinking about the relationship between income inequality and health. First, health statistics show a robust link between individual-level income and health. According to the Centers for Disease Control (CDC)'s National Health Interview Survey (2012), the age adjusted percentage of US adults who report fair or poor health decreases considerably as income increases. Nearly 28% of individuals with incomes below 100% of the poverty threshold report fair or poor health compared to 7.4% of individuals with incomes above 200% of the poverty threshold. A number of major studies also demonstrate a clear link between individual income and health, including the Whitehall Studies which find income to be related to health as a

gradient, so that every increase in income is associated with an attendant increase in health (Marmot et al 1984; Marmot et al 1978). The second strand of thinking about the relationship between income inequality and health focuses on the contextual-level. This research suggests that high levels of societal income inequality are associated with poor health outcomes. The CDC (Truman et al 2011) reports substantially fewer "healthy days" in the last 30 days experienced by individuals residing in US states with the highest levels of income inequality (17 days) compared to those who reside in states with the lowest levels (22 days). Additionally, major reviews indicate that contextual-level income inequality is negatively related to health (Wilkinson and Pickett 2009; Subramanian and Kawachi 2004).

The purpose of this research is to assess both of these strands of thought, by simultaneously examining the relationship between individual-level income and contextual-level income inequality and health. To address this research goal, I use data from the 2006 wave of the Health and Retirement Study (HRS), a nationally representative sample of Americans 51 and older. I chose to use HRS data for a number of reasons, including the large size and variability of its overall sample in income and health, and because it included all of the other variables of interest. In addition, I was able to obtain access to restricted geographic data necessary for the contextual-level portion of this analysis. Both levels of data will help me answer three over-arching research questions: 1) What influence does individual-level income have on health?; 2) What influence does contextual-level income inequality have on health?; and, 3) If there is an influence of individual- and/or contextual-level income inequality on health, which groups are most affected by it and is it a consistent effect for all?

Theoretical Explanations

The theoretical tradition that has historically been used to explain inequalities in health outcomes has been the biomedical approach (Weber and Fore 2007). Knowledge based in this tradition has come primarily from the fields of medicine, public health, and economics. Inequalities in health are well documented in this literature, especially the robust association between income and health. While those who follow the biomedical approach have over time expanded their models to include important social predictors of health, the social contexts within which individuals live their lives is still largely absent (Weber 2007). An overt sociological perspective on this problem is needed, as it is an important viewpoint into the causes and consequences of differential health outcomes (Rosich and Hankin 2010).

One of the ways that the biomedical approach differs from a sociological one is in the understanding of the mechanisms that have been thought to cause the association between income inequality and health. The biomedical tradition utilizes a general scientific approach to studying disease. In this way of thinking, the logic is linear: identify the mechanism that causes a disease and eradicate it, by which the impact of the disease is negated (or attenuated). However, the mechanism that is thought to be responsible for the association between income and health does not operate in this way. Patterns of disease throughout history suggest that mechanisms that cause poor health outcomes, such as contaminated water and the proximity of those with infectious diseases result in unequal health outcomes depending on one's economic resources. In these types of situations, wealthier individuals are able to protect their health by importing clean drinking water or isolating themselves from the source of infection.

Since poorer individuals are not able to avoid such causes of disease, they usually bear the brunt of epidemic outbreak and contagion. As mechanisms that cause diseases with unequal health outcomes are discovered and eliminated, then, those who follow the biomedical approach would expect the effects of economic resources on health to weaken. Rather, the opposite seems to be the case since the association between economic inequality and health not only persists, but is strengthened across time (Elo 2009). A sociological approach to this problem shifts the primary focus of research on health inequalities away from a cause and effect based biomedical approach, and towards examining the influence that social structures may have in shaping differential health outcomes for some groups of people (Read and Gorman 2010; Elo 2009; House and Williams 2000).

Social scientists have often explained the extent of health inequalities in a society as a result of three structural factors: 1) the differences between individuals that sort them into social strata (e.g. gender and race); 2) the differences between social strata in the distribution of resources; and, 3) the differences in the value of resources between strata (Mackenbach 2012; Grusky 2008). Structural theories predict that individuals with personal characteristics that sort them into groups lower in a stratum's hierarchy will have worse health outcomes than those sorted into groups higher in the hierarchy. Even though it is less common now to focus entirely on biological and physiological differences when researching health inequalities, these are still the main factors by which people are sorted into different individual-level social strata. In addition, economic resources in the U.S. have historically been allocated disproportionately so that Whites and men receive a greater share of economic resources than people of color and

women. On the surface, this structural explanation for the association between income, income inequality and health makes sense for middle- and older-aged individuals in the US, as there are well-documented race and gender differences in health for this population. The Department of Health and Human Services reports that older Whites (46%) are much more likely than similarly aged Blacks (26%) to rate their health as excellent or very good (AOA 2012). Additionally, these racial differences in health seem to persist with age since the health of older Blacks decreases more rapidly over time than that of older Whites (Yao and Robert 2008). A comparable gap for gender is less pronounced as women and men generally report excellent or very good health at similar rates (AOA 2012). Nonetheless, differences in health outcomes by gender do exist, as women generally face a greater share of multiple chronic conditions. Again, this disproportion persists with increasing age (Kaiser 2013).

Link and Phelan (1995) write that these differences in health exist because proximal mechanisms such as those mentioned above actually intervene on the pathway between individual resources and health, which they call the 'fundamental cause' of unequal health outcomes. For Link and Phelan, what matters the most to health is the economic resources that are available to individuals according to the strata into which they have been sorted. A second explanation that has emerged to explain the persistence of the association between income inequality and health is the Income Inequality Hypothesis (IIH). This perspective reflects the concern that a society's distribution of income may have an effect on the health of individuals. In this way of looking at this problem, those living in places where the distribution of income is highly unequal have worse health than those living in areas where the distribution is more

equal. Indeed, there is a large body of evidence to support this hypothesis (Kondo et al 2009; Wilkinson and Pickett 2009; Subramanian et al 2002; Kawachi et al 1997).

In both of these explanations, whether the most important factor is the individual-level strata or the contextual-level strata, general structural explanations hold since they match the expectations that those with a greater share of resources will have better health. However, this type of structural explanation does not account for the possibility that higher levels of income and less income inequality are not experienced equally by all. For instance, among adults within the same lower economic strata (below 100% of the poverty level) 10% more Blacks than Whites rate their health fairly or poorly (NCHS 2014). This is not just a poverty issue. For adults within the same higher economic strata (at or above 400% of poverty level) 27% more Blacks than Whites rate their health as fair or poor. Here, the value of economic resources does not transfer equally within the individual-level strata, since the same amount of resources are related to vastly different health ratings.

Why does the value of economic resources vary across strata? Lynch (2004) has proposed a “neo-materialist” theory in response to this question. This explanation synthesizes the individual income focus of the race- and gender-based strata and the contextual based strata of income distribution, as it concentrates on the effects of both. While it is still a structural explanation, the neo-materialist view focuses attention on different ways to understand the effects of larger social structures on individual health.

This dissertation addresses these competing theories by investigating the effects of individual-level income income inequality on the health of a representative population in the United States. The remainder of this dissertation is organized as follows. In

Chapter 2, I present the theoretical and empirical basis for this study. Chapter 3 describes the research design, methodology, and statistical techniques I use. Chapter 4 presents the results of the study, including relevant univariate and bivariate descriptive statistics, verification that the method chosen was appropriate for this data, confirmation of model fit, and the evidence from the statistical analysis concerning the relationship between individual-level income income inequality. In chapter 5, I interpret the findings presented in Chapter 4 and discuss potential explanations for them based on the three theories proposed in this introduction. Chapter 6 ends this dissertation with the implications and limitations of this research, along with suggestions for future research.

CHAPTER 2: THE LITERATURE REVIEW

In this chapter, I review the extant literature that documents the relationship between income inequality and health. I begin with a more in depth review of the theoretical background for this study. Then, I describe both individual- and contextual-level phenomena that have been linked to health and provide empirical evidence of relevant findings about their effect.

Theoretical Background

According to Link and Phelan (1995) and Phelan, Link and Tehranifar (2010), stratification in the distribution of individual-level social resources is the "fundamental cause" of health inequalities. These resources include knowledge, power, and money, which can be used to help individuals protect their health by avoiding diseases or diminishing the effect of disease. This theory offers a way to understand the persistence of health inequalities as Link and Phelan posit that resources such as these will "protect health no matter what mechanisms are relevant at any given time" (2010:S28). Fundamental cause theory predicts that all individuals with more resources will have better health, irrespective of their demographic positions in society. This aspect of fundamental cause theory is the most relevant to this dissertation, since this research investigates the effects of unequal amounts of income on health for certain race and gender groups.

On the contextual level, a theoretical tradition that also has considered the link between inequality and health is the Income Inequality Hypothesis (IIH). This theory suggests that health may be determined by the distribution of income within a society, and not the income of individuals (Wilkinson and Pickett 2009; Kawachi and Kennedy

1999). The IIH had its infancy with Preston's (1975) influential finding challenging the long-standing assumption that any association between income inequality and health can be fully explained by individual differences in absolute income. Specifically, he finds that for all countries with populations over two million people, increases in life expectancy at birth for the decades 1900s, 1930s, and 1960s are mostly due to increases in infrastructure and technology (i.e. contextual interventions) and not increases in absolute resources. This suggests that the same amount of relative income in some societies buys more health than in others. As a result, Preston argues that there might be a link between the distribution of income (income inequality) and life expectancy.

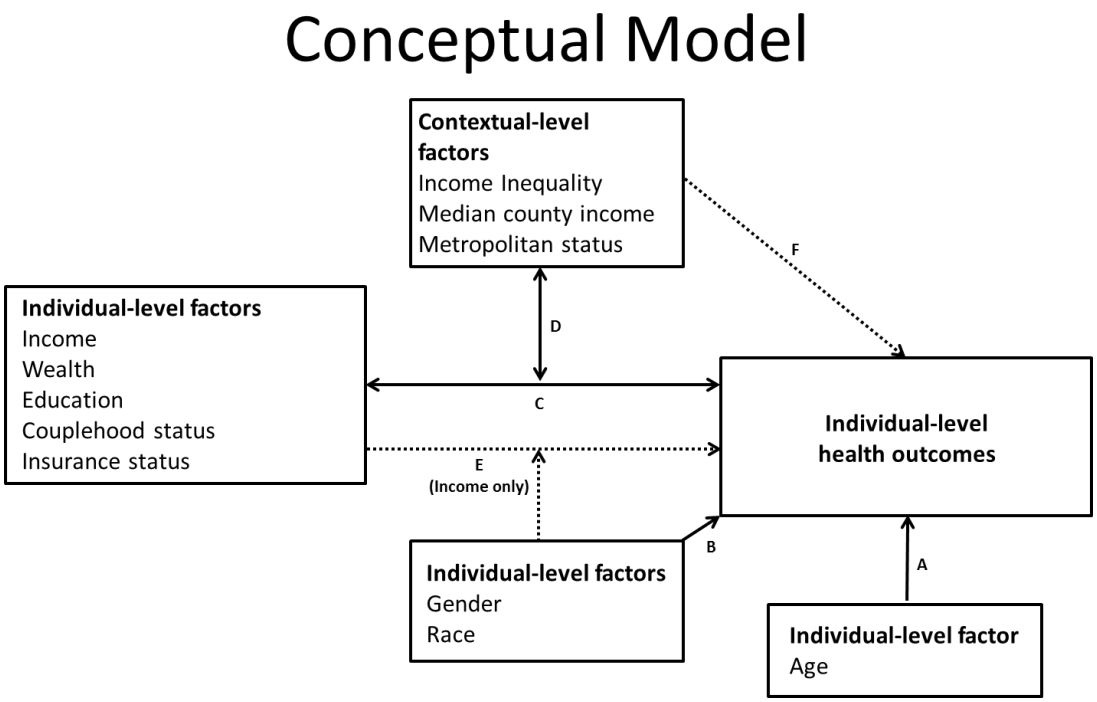
Informed partially by these findings, Wilkinson (1996) and others (Kawachi et al 1997; Subramanian et al 2002) argue that income inequality has an independent inverse effect on individual health in developed nations. Lynch et al (2004) has also proposed the neomaterial explanation for income inequality's effects on health. In this interpretation, income inequality affects health directly through the differential accumulation of material advantages and disadvantages. One contribution of this dissertation is to further consider these theoretical explanations for the relationship between income inequality and health.

Conceptual Model

Figure 2.1 is a representation of the framework I use to investigate the relationship between income, income inequality and health. The two boxes on the bottom of the model contain individual-level characteristics that have been thought to be determinants of health. Their effects are represented by uni-directional Line A and Line

B. Gender and race have been thought to shape modern economic inequalities (Read and Gorman 2010), while the fact that health decreases with age is not surprising.

Figure 2.1: Conceptual Model



The leftmost box in the model contains other individual-level characteristics that have been linked to disparate health outcomes. Rather than determining health, though, there is evidence that supports the idea that causes of poor health may flow both ways between these factors and health. While, generally, low economic resources are thought to be a cause of poor health outcomes, it may also be true that poor health causes someone to have low income. For example, an individual in poor health may not be able to find a job or, even if they are employed, may have to expend a great deal of their income on medicine or medical bills. These linkages are represented by the bi-directional line C. The box at the top of the model contains the contextual-level factors that are used in this research. These factors are represented with bi-directional Line D

because they have been thought to interact with any number of individual level factors to create a multiplicity of possible health outcomes.

The model proposes two other pathways between income and income inequality. Dotted line E represents a pathway from gender and race that flows through the effect of income on health. This line will be tested by examining the effects of income on health. Evidence to support the existence of this line would be found if the effect of income on health varies across race and gender group. Dotted line F represents a proposed pathway from the contextual-level variables to individual health. It represents the independent effects that income inequality may have on health, separate from individual income. This line will be tested by examining the effect of the contextual-level factors on health. In the next section, I discuss how each individual- and contextual-level factor has been conceptualized, and include evidence from the literature that links them to inequalities in health outcomes.

Dependent Variables

According to Link and Phelan (1995) and Phelan, Link, and Tehranifar (2010), a variable must affect multiple health outcomes to be considered a fundamental cause of health. Thus, I use a multidimensional conceptualization of health with three distinct measures. Health is an abstract concept that includes not only institutional definitions (e.g. the presence or absence of a medical diagnosis) but also cultural definitions (e.g. the limitations that such a diagnosis may have on an individual's ability to function). Jylhä (2009) writes since health is dependent on context, attempts to capture it must include both its institutional and cultural understandings. The institutional aspect of health status generally includes a physician's diagnosis based on symptoms and

physical assessment, while cultural understandings include not only survival but also being able to function (Jylhä 2011). For this reason, I use self-rated, physical, and mental indicators of health in order to reflect these institutional and cultural meanings.

Self-rated indicator of health

Self-rated health (SRH) has been one of the most frequently used indicators of health in social research (Jylhä 2011). In perhaps, the most extensive review of SRH, Idler and Benyamini (1997) examine 27 studies of representative populations. They find self-rated health independently predicts mortality, net of a number of relevant covariates—including socio-demographic variables. They also find that SRH is more predictive of death in the elderly than physical assessments by their physicians. Others suggest caution, though, that SRH levels may not be directly comparable for individuals of different income levels (Dowd and Zajakova 2007) and race and age groups (Dowd and Todd 2011).

Physical indicator of health

Institutional definitions are an important component of health as they capture the condition of the human body. This includes indicators for diseases that may put an individual at risk for death (e.g. heart disease, cancer, diabetes, hypertension) or conditions that affect the way they function in life (e.g. arthritis). The literature shows little evidence of a robust universal association between specific diseases or conditions and membership in a specific race or gender group, as the associations between incidence of disease or condition vary across groups. While it does seem that Blacks generally have worse outcomes than Whites, this relationship often varies by gender (Schiller et al 2012). The literature shows that in general women live longer but have

worse health than men, especially as they age. For example, the Kaiser Foundation (James et al 2009) found that 40% of women 65-74 have 3 or more chronic conditions, compared to 35% of men, while those 85 and older had rates of 63% and 51%, respectively.

Mental health indicator

The cultural aspect of health status includes indicators of mental health, such as depression. Depression is measured by symptoms that include difficulties with sleeping, concentration, sadness, hopelessness, worthlessness, loss of interest or pleasure in doing things, and feeling like everything is an effort (NCHS 2011). Compared to the physical indicators of health, the relationship between race, gender and depressive symptoms is much more robust. Whites generally have a lower frequency of depressive symptoms compared to Blacks (Schiller 2012). There is also a fairly clear gender-specific association, with women generally having higher frequencies of depressive symptoms than men (Pratt and Brody 2014). These relationships can be quite complex though, as Black men are more likely than Black women to report depressive symptoms on specific indicators, such as worthlessness and feeling like everything is an effort (Schiller 2012). As opposed to physical health, a recent report from the CDC (2014) shows that depression falls with increasing age. In this study, middle-aged women are shown to have the highest rate of depression but that this rate falls by almost a third as they age. Middle-aged men also had a higher rate of depression than their older counterparts with a rate over double that of older men.

Independent variables

This study examines the contribution of both individual- and contextual-level social phenomena that research has shown to affect health. Race and gender are predictor variables in the overall analysis in this research, but I also use stratified analysis to examine their intersection to detect how the effects of individual-level income income inequality vary for White men, White women, Black men, and Black women.

Individual-level economic predictor and control variables: Income and Wealth

Income is typically conceptualized as the flow of money earned over time while wealth is all owned assets, minus debt, at one single point in time. Often, the two are thought of interchangeably, but it is important to differentiate between them as they capture different aspects of economic position (Brandolini and Smeeding 2008). Whereas House and Williams (2003) argue that income is the most reliable predictor of health as the effects of other measures (e.g. education and wealth) are at least partly mediated by income, Keister (2014) argues that wealth may be a more advantageous predictor than income because the effects of wealth ownership are more extensive. This is so, she writes, because wealth represents economic reserves that may be used as a buffer against sudden economic changes, such as unemployment or other types of emergencies.

Income and wealth amounts are most widely measured with household surveys and administrative records (Stone, Trisi, and Sherman 2013). Each source has its own benefits and limitations. Household surveys offer extensive details about each respondent in a representative sample but most lack the ability to capture data in the extreme tails of the income distribution, especially the tails that include data about the

extremely rich (McCall and Percheski). This is due to the fact the very rich are unlikely to participate in survey research (Brandolini and Smeeding 2008). Alternatively, administrative records (e.g. US income tax data) do include data about upper income individual. However, since tax filers in general have higher incomes than non-filers they may not be representative of the US population. Administrative records also lack the individual demographic detail that is necessary to make generalizations.

Surveys and administrative records measure income in many ways, including measures of central tendency and variability. Contextual-level income inequality is commonly measured with summary statistics, such as the Gini coefficient used in this research. I will discuss this widely available measure in the "Income inequality" section later in this chapter. Unfortunately, there is no accessible summary statistic to measure contextual-level wealth inequality for different geographic aggregates. As such, I am not able to use wealth as a predictor variable in this research as it would not be directly comparable to the contextual-level measure of income inequality. Consequently, in this research, I use income as an individual-level economic predictor variable and wealth as a control variable.

Individual-level control variable: Education

Many social scientists consider education to be the best way to reduce health inequality in the US, as education has a consistent and robust association with health (Elo 2009). In the case of mortality, for instance, Kitagawa and Hauser (1973) match death certificates with people who had died from May to August of 1960 with records from the 1960 census. They find that mortality from all causes is inversely associated

with educational attainment, so that those with higher educational attainment have lower rates of mortality than those with lower educational attainment.

The association between education and health has also been examined for race and gender differences. Elo and Preston (1996) use the National Longitudinal Mortality Survey (NLMS) to examine educational differentials in health and find that differences in education have an adverse effect for both women and men but that the magnitude of effect is greater for men. Zajacova and Hummer (2009) link data from the National Health Interview Survey to the National Death Index and find there are no systematic gender differences between white men and women that are not explained by other variables, and no difference at all between black men and women.

Individual-level control variable: Age

The relationship between age and physical health is well established, with evidence of a positive relationship between age and many diseases and conditions (e.g. heart disease, hypertension, stroke, cancer, arthritis). As age increases so does the percentages of individuals diagnosed (Schiller et al 2012). The relationship between mental health and age is less clear than those for self-rated and physical health, though. The CDC (2008) estimates that 20% of people in middle age experience some sort of ongoing mental health concern. The Administration on Aging in the Department of Health and Human Services (2013) approximates that 15-20% of older adults in the US have experience depression at some point in their life. Health experts are not only concerned with the implications that depressive incidents can have for the mental health of older people, but also the consequences that they may have for physical health, as well. For instance, even mild episodes of depression lower immunity and may diminish

a person's ability to fight off infections or other physical ailments that affect older individuals (Karel et al 2012). There is also a paradox concerning the relationship between age and mental health in that adults aged 50-64 report more episodes of depression than adults aged 65 or older (CDC 2008).

Individual-level control variable: Couplehood status

Previous research shows that being married or in a marriage-like relationship is generally protective of health (Lillard and Waite 1995; Mirowsky and Ross 2003). Pienta, Hayward, and Jenkins (2000) use nested logistic regression models with Health and Retirement Study (HRS) data to find that married individuals nearing retirement have the lowest rates of morbidity than non-married individuals, including those who are divorced, widowed, and never married. Also using HRS data, Hughes and Waite (2009) examine how the experience of marital disruption affects health, finding that those who are divorced or widowed and have not remarried have worse health than who are married. Others write that the nature of the marriage relationship is more important to the health of middle- and older-aged individuals than the mere presence of a spouse or long time cohabitating companion (Bookwala and Jacobs 2004).

Individual-level control variable: Insurance status

Insurance status can affect health through access and quality of care, especially concerning the public vs. private nature of the source of the insurance. In general, individuals with public forms of insurance (eg. Medicare, Medicaid, VA) have worse health than those with private or employer insurance. Caution should be used when making any further generalizations about this measure, though since these categories are not necessarily discrete since people can have more than one type of insurance.

Contextual-level control variable: Median County Income

Aggregate county income is added as a contextual-level control variable as it has been shown to have an independent effect on health (Anderson et al 1997). Such effects may reflect material resources that may intervene in the relationship between the Gini coefficient and health. The association between individual income and health may also be affected by higher median county income above and beyond that of individual-level resources (Blakely et al 2002).

Contextual-level control variable: Metropolitan status

Living in a community that is considered disadvantaged has health consequences. Ross and Mirowsky (2001) link data from the 1995 Community, Crime, and Health Survey to a respondent's census tract to find that the level of disadvantage in a neighborhood is positively associated with poor health, so that as the level of disadvantage increases, so does poor self-rated health and a number of chronic physical health conditions. Robert and Lee (2002) found that in combination with individual-level resources, the characteristics of the community in which older Black Americans live more fully explains their disproportionately higher numbers of chronic diseases than individual resources alone. Massey and Denton (1993) argue that such results are due to residential racial segregation, which separates blacks into geographically concentrated poor neighborhoods in metropolitan areas. There are other many ways that such segregation can affect health, such as limiting access to jobs and job preparation (Braveman et al 2012), which, in turn limit income and wealth accumulation.

Contextual-level predictor of income inequality: Gini coefficient

Even though numerous studies find that individuals living in more unequal societies are at greater risk for poor health than those living in more equal societies, the

effects of contextual-level income inequality on health is nowhere near to being a settled topic. Some scholars reject the hypothesis that income inequality is detrimental to individual health (Deaton 2003), while others write that it may even improve health (Mellor and Mylio 2001). Research examining the economic factors that influence health has traditionally focused on individual-level measures of income and wealth. This broad literature has been labeled the “absolute income effect” (Wagstaff and van Doorslaer 2000). Figure 2.2 shows this effect as being a gradient which supposes that there are increasing health returns at each increase in income.

Figure 2.2: Health gradient

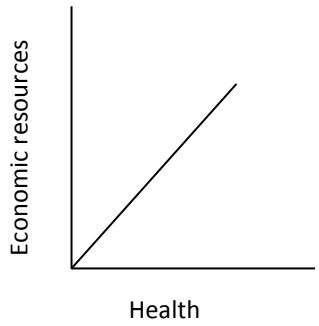
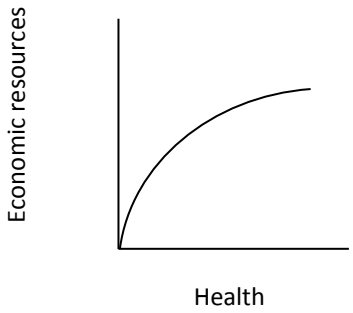


Figure 2.3: Arc of diminishing health returns

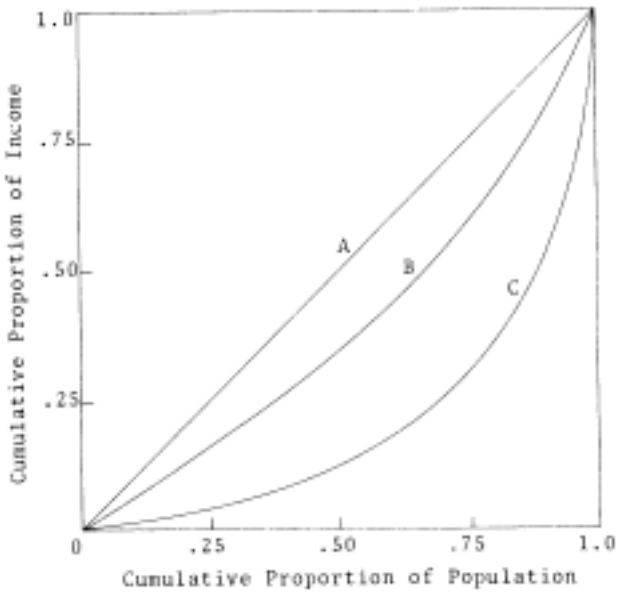


Mackenbach et al (2000) have challenged the gradient aspect of the relationship between health and income by arguing in favor of a curvilinear relationship instead. As shown in Figure 2.3, the shape of the relationship between income is not a gradient but a concave arc. This means that rather than being linearly related to income, there might instead be a diminishing health return as income values rise.

Contextual-level income inequality measures the gap in income between groups in a society. The most commonly used summary statistic of income inequality is the Gini coefficient, although comparisons between Gini estimates and other measures (e.g.

Thiel and Atkinson indexes, and the coefficient of variation) are highly correlated (McCall and Percheski 2010). The Gini coefficient (also commonly referred to as the Gini index) is based on the Lorenz curve, as seen in Figure 2.4.

Figure 2.4: The Lorenz Curve

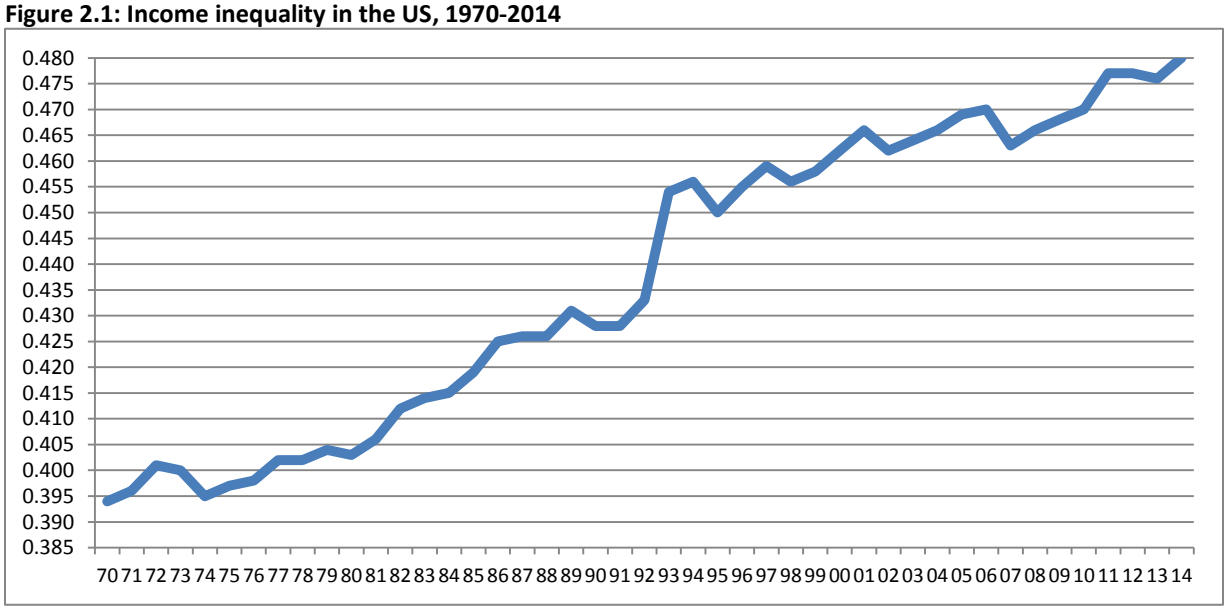


source: Allison (1978)

The Lorenz curve represents a cumulative distribution of a resource. The units of analysis in the population (e.g., individuals or households) are plotted on the x-axis and the distribution of income or wealth (or whatever distributional unit being analyzed) is plotted on the y-axis. One possible distribution of income is represented by line A, the 45º line bisecting the graph. Lines B and C represent two other possible distributions. The Gini coefficient is calculated as a ratio of the area within the curve of Lines B and C to the total area under Line A. The distribution represented by Line A is one where there is no gap between the distribution of population and income (e.g. if 10% of earners combine to receive 10% of a population's total income). This is a line of perfect equality

and the Gini coefficient is 0. Both lines B and C deviate from the line of perfect equality but as Line C deviates more it's Gini coefficient will be greater than B's. Maximum inequality would be a distribution where a single individual receives all the income and the Gini coefficient would be 1. As can be seen in Figure 2.5, since 1970 the Gini index in the U.S. has grown steadily from 0.394 to its most recent amount of 0.480 (OECD 2014). To put this index in context, the U.S. Gini coefficient for 2014 is fourth highest among the 34 members of the Organization for Economic Cooperation and Development, behind only Chile, Mexico, and Turkey (OECD 2014).

Figure 2.1: Income inequality in the US, 1970-2014



Source: US Census Bureau: Table IE-1 and Table A-2 in DeNavas-Walt et al 2014.

The evidence of a relationship between income inequality and health is mixed. In their extensive review, Wilkinson and Pickett (2006) report that over ¾ of the 168 analyses they reviewed are either fully or partially supportive of IIH (See Table 2.1). When that review is narrowed down to just the 86 studies that focus on the US, including large areas like census regions or smaller areas like counties, 45 were fully

supportive, 26 were partially supportive, and 15 where completely unsupportive of the IIH.

Table 2.1: Analyses of the relationship between income inequality and health

Evidence of association between Income Inequality and Health (Wilkinson and Pickett 2006)			
	Number of analyses reviewed N=168	US focused N=86	Multi-level modeling as method N=27
Wholly supportive (Only significant positive findings)	87	45	8
Partially supportive (Some significant positive and some null findings)	44	26	10
Completely unsupportive (No significant positive findings)	37	15	9

Subramanian and Kawachi (2004) suggest at least two reasons for this lack of consensus. First, many studies on this topic have design issues such as low sample sizes (for population based research) or missing data. For example, one of the 26 partially supportive studies from Table 2.1 (Blakely et al 2002) finds a small association between county level income inequality and self-rated health, but the authors report having complete Current Population Survey (CPS) data for only 59.3% of their 18,547 respondent nested within 216 out of about 3,200 US counties. A second possible reason for the inconsistency of evidence concerning the ICC is that in the majority of the studies reviewed, the investigators do not account for the hierarchical nature of their data. This argument is supported in Table 2.1, since only 8 of the 45 fully supportive and 10 of the 26 partially supportive studies used multi-level modeling as their research method.

In this chapter I review the current state of the literature concerning the relationship between income, income inequality and health. The next chapter details the methods, data, measures, and statistical tools I used to examine this relationship.

CHAPTER 3: METHODOLOGY

This study uses data from The Health and Retirement Study (HRS), RAND Corporation, and The American Community Survey (ACS) to assess individual- and county-level associations between income inequality and three measures of health for a representative population of the US.

Data Sources

The Health and Retirement Study (HRS) is a full panel study that is conducted every two years. The study began in 1998 when the original HRS cohort merged with the Study of Assets and Health Dynamics Among the Oldest Old (AHEAD). Since then, four refresher cohorts have been added over 13 waves and the full current HRS sample consisting of over 26,000 respondents. The health and demographic data in the public use files of the HRS can be freely downloaded at http://hrsonline.isr.umich.edu/. To insure respondent confidentiality, though, use of geographic data is restricted and not available publicly. I obtained permission from the HRS Case Review Group to access data in the geographic and mobility files. Data used for this study are from the final release of the 2006 wave.

I used income and wealth measures from RAND, which are available online at http://www.rand.org/labor/aging/dataprod/hrs-data.html. RAND is a not for profit corporation whose Center for the Study of Aging explores the ways that global economic policy can affect populations. For this study I obtained cleaned individual-level income and wealth data, which RAND imputes from the HRS household-level data. Missing data is calculated from existing data.

The third data source of data for this research is the American Community Survey (ACS), conducted by the U.S. Census Bureau, and its data is publicly available for download at http://www.census.gov/acs/www/. For this research, the 2006 1-year estimate of the Gini coefficient for US counties was matched by its FIPS (Federal Information Processing Standards) code to the restricted geographic HRS data. FIPS codes are the standard way to uniquely identify US geographic areas.

Sample

The unit of analysis for the HRS sample is a household financial unit that includes at least one age-eligible person. This could mean a household with a single unmarried age-eligible person or a household with at least one age-eligible person. If one member of the household is age-eligible, their spouse is automatically selected whether they are age eligible or not. If more than one age-eligible unrelated people live in a household, one of them is randomly selected to be the household financial unit to be followed in the study.

Two common sampling techniques are used to generate the HRS sample: an area probability method to produce what is known as “the core sample” and an oversample of special populations to ensure representativeness.

Core Sample

The core sample is selected in a 4-step process. First, using a probability proportionate to size method, Primary Sampling Units (PSUs) are selected from a sampling frame identified by researchers at the Institute for Social Research at the University of Michigan in Ann Arbor, Michigan. PSUs are located in both metropolitan (MSA—Metropolitan Statistical Area) and nonmetropolitan (non-MSA) counties and are

structured into 84 stratums according to size. Next, a second area probability method is used to identify a predetermined number of Secondary Sampling Units (SSUs) within each PSU. Then, all the housing units (HUs) in each PSU are enumerated. In practice, this means that an HRS field representative drives or walks through each SSU and physically evaluates each HU (i.e. single-family or multi-family units) for suitability of inclusion. From the list of suitable HUs, a pre-determined number are systematically selected for further contact by the field representative, who visits every selected HU to assess whether an age-eligible person lives in that HU. If so, they attempt to enroll them, and their spouse (if applicable) in the study. If no age-eligible person lives in the HU, or if the person declines to participate, the representative goes to the next selected HU, until the required number of individuals from that SSU are enrolled. The rate of those initially contacted who agree to enroll is fairly high (ranging between 69.9% and 81.6%) and equally, as stable since 85%-93% of participants agree to cooperate in follow-up waves (HRS 2008).

Oversample

An oversample of special populations is taken in order to better represent populations that have historically been underrepresented in social research. Blacks and Hispanics are oversampled 2:1 by adding supplemental SSUs to PSUs with a high density of such households.

Special Population

Due to a design choice made by initial investigators, women over age 50 are also uniquely represented in the HRS. Unlike earlier population based longitudinal retirement studies, such as the Social Security Administration's 1969-1979 Retirement History

Study, initial HRS investigators did not view the male worker as the sole unit of analysis. Rather, they thought that the spouses or partners of workers were important additional sources of influence and treated them as respondents in their own right (HRS 2008). Since those earlier studies had been conducted during a time when the prevalence of women working outside the home was low compared to current rates, this meant that the role of women in decisions made about health and retirement issues was largely ignored. As the number of women who have become age eligible workers themselves has expanded dramatically since the HRS began in 1992, this data source is distinctively representative of middle- and older-aged US women in both the private and the public spheres.

Other considerations

There are seven other considerations that affect the sample used in this research. First, while there are some younger adults in the full sample (as they were automatically enrolled as spouses or partners of age eligible respondents), only those age-eligible themselves are included in the HRS representative sample. Age-eligible means all respondents born before 1954. Second, if a respondent is physically or mentally unable to participate in the interview on their own, the HRS allows a proxy to complete it for them. Since the indicators that comprise the mental health measure ask a respondent to evaluate his or her own state of mind, the HRS does not ask these questions of proxy respondents. Therefore, this research excludes proxy interviews as they are missing the data for one of the outcome variables. Third, in 2006 the ACS did not release a 1-year Gini estimate for the county of residence for all sample members. Since this measure is vital to this research, every respondent included in the analysis

had to have a Gini estimate. Therefore, 18 cases of sample members living in a county with no Gini estimate available are excluded. Fifth, this research only includes non-Hispanic Blacks and non-Hispanic Whites since there weren't enough respondents in each county who self-selected into the Hispanic and Other race categories for statistical analysis. Sixth, the HRS is not representative of nursing home residents so they are not included in this analysis. Finally, complex sampling weights are used to ensure the study is representative of the older US adult population. The HRS assigns weights based on the strata and cluster of the PSU and SSU of a respondent's geographic location. They are accounted for in the statistical analysis with the use of the individual-level 2006 wave specific weight for 14,126 respondents.

Measures and Variables—Dependent Variables

Self-rated health

SRH is assessed with one measure from the HRS, where participants are asked, "Would you say your health is excellent, very good, good, fair, or poor?" The measure is continuous, where excellent=5, very good=4, good=3, fair=2 and poor=1. In order to be consistent with the direction of magnitude in the physical and mental health measures, these response options are recoded so that higher numbers represent worse health and lower numbers represent better health.

Physical health

I measured physical health continuously with an index of the 5 most frequently occurring conditions or diseases affecting older persons: arthritis, heart problems, cancer, diabetes and hypertension (AOA 2013). These measures are from the HRS, where respondents are asked if a doctor had ever diagnosed them for the disease. A

reported diagnosis of a condition or disease is coded “1” and the absence of a diagnosis is coded “0”. The value for each individual condition or disease is then summed. This index ranges from 0-5 and higher values mean the respondent reports more health conditions or diseases.

Mental health

Psychological and social stresses are also factors that can affect one’s overall health. I measure this as a continuous variable with the commonly used Center for Epidemiological Studies—Depression (CES-D) scale. This measure is from the HRS. To determine symptoms of depression each non-proxy respondent is asked the following eight questions (with response options of “yes” or “no”): Much of the time during the past week….1) I felt depressed; 2) I felt everything I did was an effort; 3) My sleep was restless; 4) I was happy (reverse worded); 5) I felt lonely; 6) I enjoyed life (reverse worded); 7) I felt sad; and 8) I could not get going. The total number of “yes” responses to questions 1, 2, 3, 5, 7, 8, and the “no” responses to questions 4 and 6 were summed to arrive at a CESD score that ranges from 0 to 8, where higher numbers represents more psychological and social stress.

Measures and Variables—Independent Variables

Both individual- and contextual-level factors are included as independent variables. Individual-level measures are gender, race, income, wealth, education, age, couplehood status, and insurance status. The contextual-level factors are measures of median income, metropolitan status, and income inequality for the county where each respondent lives. Each of these variables is included in this study based on the empirical literature previously discussed, not due to empirical analysis of the HRS data.

Gender

Gender is assessed at the time of HRS enrollment interview and is coded as female=1; male=0. The term gender is often used in studies of health inequalities when the researcher is really interested in sex-based differences in rates of morbidity and mortality. This research follows the feminist informed definition of gender, so that the biological categories of female and male are understood to represent the social categories of women and men, respectively.

Race

Similarly, the race categories used in this study do not capture biological difference, but rather socially constructed classifications that reflect cultural and ethnic diversity (such as language, beliefs, and values). Upon enrollment in the HRS, participants self-select into as many race categories as they wish, which are then masked into: White/Caucasian, Black/African American, and Other (Asian, American Indian, Alaska Native, Native Hawaiian, and Pacific Islander). Ethnicity is also assessed at time of enrollment, with participants selecting one of these 4 categories: Hispanic—type unknown, Mexican American, Other Hispanic, or Not Hispanic.

I include only non-Hispanic White and Black individuals in this research, as the number of respondents selecting into the “Other” and “Hispanic” categories are insufficient. In order to protect respondent confidentiality, HRS protocol asks analysts to avoid using cross-tabulation cells with less than 3 respondents in them. Of the 863 counties in this research that had geographic data for those in the representative sample, only 68 had 3 or more Hispanic respondents (7.8%) and only 31 had

respondents who selected into the “Other” category (3.5%) living there. To comply with the protocol, these respondents were dropped from the sample.

Race is coded dichotomously, where 0=White and 1=Black. I also account for the intersection of race and gender with an inclusive variable where 0=White men, 1=White women, 2=Black Men, and 3=Black women. Although this coding is continuous, I treated this variable as categorical in all analyses. This variable is used in the stratified section of the analysis.

Income

RAND calculates income as the sum of all earnings, pensions, and Social Security. The original distributions for both the income and wealth variables violated the assumption of normality necessary in statistical analysis. To correct for this, I used natural logarithm transformation for both variables. Since some respondents had no income and the natural logarithm of zero cannot mathematically be calculated, I added $1 to the income of all respondents. This transformation made it possible to calculate the natural logarithm for all respondents but did not change the distribution in any substantial way.

Wealth

Wealth is calculated by RAND as the sum of all assets minus the sum of all debts. Assets are property (like houses and vehicles) and holdings (like stocks or mutual funds), while debts are liens or mortgages on property, along with home equity loans and credit cards. The natural logarithm of wealth is used. As it is impossible to calculate the natural logarithm of a negative number, for respondents with more debt

than assets I calculated the absolute value of the natural logarithm of wealth and then multiplied by -1 to return the wealth value to its formerly negative state.

Education

In this research, education is assessed at time of enrollment. Those with no formal education are scored as 0. Grades 1-11 are continuously measured according to the number of years a respondent had of formal education. A value of 12 means that the respondent is a high school graduate, while 13-15 means they had some type of college education. College graduates have the value 16 and those with advanced degrees (MD, DO, JD, MA, PhD) have the value of 17. For the purposes of this research, and as is the conventional way this variable is used, the number of years of education is treated as a continuous variable, so that higher numbers of years in school represent more education.

Age

Age is measured continuously and is assessed at time of enrollment. Respondent age used in this research is age at the time of the 2006 interview.

Couplehood status

Each respondent's coupled status (e.g. whether a respondent is married or part of a marriage like relationship) is from the HRS and is assessed with each wave to account for changes in status. It is a dichotomous variable, where one means a respondent is coupled and zero means they aren't coupled.

Insurance status

Respondent insurance status is measured with a series of dichotomous variables that ask about 5 types of insurance. This data is from the HRS and is assessed with

each wave to account for changes in status. These variables are not necessarily mutually exclusive because it is possible for respondents to have more than one type of insurance. However, there is a mutually exclusive variable for no insurance for respondents who report none of the 5 types of insurance included in this research. Each measure in this section is coded 1 if respondents have that type of insurance and 0 if they do not. In the case of the no insurance item, 1=no insurance and 0=insurance.

Metropolitan status

The Beale Rural-Urban continuum classifies metropolitan statistical areas (MSAs) according to population and non-MSAs according to both population and proximity to a MSA. This data is from RAND was matched to the masked county codes. The definitions for each category are shown in Table 3.1. The continuum ranges from 1-9, where 3 categories represent metropolitan counties and 6 categories represent non-metropolitan counties. These categories are then collapsed into a dummy variable, where metropolitan residence is coded as 1 and non-metropolitan residence is coded as 0. The terms “metro” and “non-metro” are used intentionally to indicate that this measure is a location descriptor, as opposed to “urban” and “rural”, which are often used as racial descriptors.

Table 3.1: Beale Rural-Urban Continuum codes*

Metro Counties	
9	Counties in metro areas of 1 million population or more
8	Counties in metro areas of 250,000 to 1 million population
7	Counties in metro areas of fewer than 250,000 population
Non-metro Counties	
6	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
4	Urban population of 2,500 to 19,999 adjacent to a metro area
3	Urban population of 2,500 to 19,999 not adjacent to a metro area
2	Completely rural or less that 2,500 urban population, adjacent to a metro area
1	Completely rural or less that 2,500 urban population, not adjacent to a metro area

*Reverse coded so higher numbers represent greater population

Median county income

Median county income is from the ACS for each conterminous U.S. county and was matched to the restricted geographic data for each participant's county of residence. It is a continuous variable and in order to be consistent with the measurements of income and wealth, the logged value is used.

Income Inequality

The county-level measure of income inequality was obtained from the ACS and is measured with the 2006 1-year estimate of the Gini coefficient. The ACS also releases a 5-year estimate for the years 2006-2010. However, the 5-year estimate is not released for all of counties with 2006 estimates. Since using the 5-year estimate would result the loss of 2,634 respondent with a 2006 1-year estimate but no 2010 5-year estimate, and the fact that there was no meaningful difference between the key descriptive statistics for the two estimates, I use the 2006 estimate.

The Gini coefficient is a continuous variable and is matched to the masked Federal Information Processing Standard (FIPS) county identifiers from the HRS geography and mobility file. In order for the coefficients in the regression models to be on an interpretable scale, I multiplied the ACS Gini estimates by 100. So, instead of ranging from 0-1, the variable now ranges from 0-100, where counties with higher coefficients represent more inequality and counties with lower coefficients represent less inequality.

Statistical Analysis

Assumptions

Missing demographic data was limited to 17 cases with missing education values. Education level for these respondents was imputed using the sample mean (12.96). To assess whether the assumptions of parametric data had been met, I first checked for normality, homogeneity of variance, and independence. To test for normality, I checked frequency distributions and measures of central tendency in the data. Extreme skewness and kurtosis existed for wealth and income so these values were logarithmically transformed in order to produce acceptable distributions (described above). There were no other outliers (+/- 3.10 SD) in any of the other predictor variables. The distribution for the mental health outcome was also very skewed. The steps I took to deal with this potential violation of assumptions are described in Chapter 4. To test for homogeneity of variance, I used Levene's test in a one-way ANOVA. I also tested for significant group mean differences using ANOVA. The assumption of independence of errors is addressed below, in the discussion concerning the multi-level models used in this statistical analysis.

Multi-level modeling

For this analysis, I used multi-level modeling (MLM) using the SPSS (v. 22) MIXED command with fixed and random intercepts to assess the relationship between income inequality and 3 measures of health for a representative sample of middle- and older-aged residents in the US. Multi-level models are generally used when data is collected at different levels (e.g. for individuals living in counties) to avoid violating the assumption of independence necessary in standard regression techniques (Hox 2010).

In the case of this research, this means that the health of individuals may be more similar to those living in closer geographic proximity to them than to the health of those living farther away. These similarities could be due to shared background experiences, mutual environmental influences, or clustering of certain demographic and/or economic groups. If these non-randomly distributed individual-level characteristics are present in this data, and standard regression models are used, it is possible that these communal influences are responsible for any differences observed in health outcomes, rather than the hypothesized predictor variables.

MLM recognizes the hierarchical nature of this type of data by allowing for residual components at each level in the hierarchy. In this way, measurements at one level are not dependent on the measurements at another. For these hypothesized models, MLM allows for the grouping of respondent health outcomes within each county into two error residuals, one each for the individual- and county-level. This is due to the error term being partitioned into a within county component (the variance of the individual-level residual) and a between county component (the variance of the county-level residual).

Analysis

I use a two-level hierarchical model to assess the effects of income inequality on health. I expect that high levels of inequality are positively related to poor health outcomes. At level-1, the units I model are the 3 health outcomes with relevant individual-level demographic and economic covariates for each of the 14,126 representative respondents, while at level-2 I also explore the influence of the economic context associated with that of the 863 counties where the respondents live. The

equations used to estimate the multi-level models are presented below, using Raudenbush and Bryk's (2002) standard notation. I include self-rated health (SRH), income, and the Gini coefficient as examples to aid in interpretation.

$$\Upsilon_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij} \qquad \text{(Equation 1)}$$

Equation 1 represents a level-1 model with one individual-level predictor (income) of respondent health (SRH), where Υ_{ij} is the SRH of respondent i in county j, β_{0j} is the intercept (average) of SRH for county j, X_{ij} is the income of respondent i in county j and β_{1j} is the slope (or regression coefficient) associated with X_{ij}—which is the value that represents the relationship between income and SRH. The last term in the equation, e_{ij}, is the individual-level error term, which is assumed to be normally distributed.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \mu_{0j} \qquad \text{(Equation 2)}$$

$$\beta_{1j} = \gamma_{10}$$

Equation 2 represents the level-2 model with one county-level predictor (Gini) where γ_{00} is the intercept that represents the grand mean of SRH across individuals across counties, W_j is the county-level Gini for county j and γ_{01} is the regression coefficient associated with W_j, μ_{0j} is the error term representing a unique effect associated with county j, and γ_{10} estimates the average effect of the Gini coefficient. The absence of covariates in the equation for β_{1j} indicates that the effect of Gini is fixed, or held constant across counties, and the lack of an error term indicates that the effect

of income is not specified to vary randomly across counties. This type of model is commonly referred to as a “random intercept” model.

The full level-1 overall model for SRH, then, is:

$$(\mathrm{SRH})_{ij}=\beta_{0j}+\beta_{1j}(\mathrm{race})_{ij}+\beta_{2j}(\mathrm{gender})_{ij}+\beta_{3j}(\mathrm{income})_{ij}+\beta_{4j}(\mathrm{wealth})_{ij}+$$

$$\beta_{5j}(\mathrm{education})_{ij}+\beta_{6j}(\mathrm{coupled\ status})_{ij+}+\beta_{7j}(\mathrm{insurance\ status})_{ij}+\beta_{8j}(\mathrm{age})_{ij}+e_{ij}$$

and the level-2 model is:

$$\beta_{0j}=\gamma_{00}+\gamma_{01}(\mathrm{Gini})_{j}+\gamma_{02}(\mathrm{median\ income})_{j}+\gamma_{03}(\mathrm{metro\ status})_{j}+\mu_{0j}$$

$$\beta_{1j},\ldots,\beta_{kj,}=\gamma_{10},\ldots,\gamma_{k0}$$

In this model, k = 1,…,8, corresponding to each of the 8 covariates in the model. Lastly, in addition to the overall models, I also stratify them by gender and race (White men, White women, Black men, and Black women).

Hypotheses

The relationship between income inequality and health is analyzed to test these hypotheses:

H1: Based on Link and Phelan’s structural theory of fundamental cause, there is a positive association between individual-level income and self-rated, physical, and mental health.

H1a: If H1 is supported, fundamental cause theory will predict that the value of this positive association would benefit individuals in groups that are higher in the social hierarchy (e.g. White men) than those in groups that are lower in the hierarchy.

H2: Based on the ICC, there is a negative association between contextual-level income inequality and health.

CHAPTER 4: RESULTS

This chapter summarizes the results of the multivariate statistical analysis used to examine the relationship between income inequality and health, as measured by physical, self-rated, and mental health. In this chapter, I explain the procedures I used to obtain these results, as well as present relevant tables and summary statistics. In the next chapter I will interpret these findings in the broader context of sociological theory. In section one, I present statistics to describe the sample. Second, I assess whether the choice of multi-level modeling was the appropriate method to use for this research. In section three, I report the overall and stratified results of the multi-level models that predict the effect of income inequality on health.

On the individual-level, I use Link and Phelan's theory of fundamental cause to predict that those with less income will have worse health outcomes than those with more. On the contextual-level, I use the Income Inequality Hypothesis (IIH) to predict that health can be negatively affected by an unequal distribution of income, even when accounting for one's individual income. Accordingly, I expect that individuals living in counties with higher income inequality will have worse health outcomes than those in counties with less inequality. I also use Neo-materialism theory to examine whether the effects of any hypothesized individual- or contextual-level relationships are the same for all individuals.

Results section I: Descriptive statistics

In this section, I present the results of the descriptive statistics for each outcome (self-rated, physical, and mental health), predictor (income and Gini coefficient), and

control variable (gender, race, education, age, coupled status, insurance status, wealth, median county income and metro status).

Table 4.1: Weighted Means Standard Deviations, or Percents for all variables

	Total Sample		White Men		White women		Black men		Black women	
	N=14,126		N=5,101		N=6,853		N=767		N=1,405	
	Mean/		Mean/		Mean/		Mean/		Mean/	
	Percent	SD	Percent	SD	Percent	SD	Percent	SD	Percent	SD
Dependent Variables										
Self-rated health	2.71***	1.105	2.64***	1.090	2.68***	1.101	3.04***	1.139	3.21***	1.048
Physical health	1.65***	1.186	1.59***	1.208	1.65***	1.155	1.67***	1.245	2.02***	1.177
Mental health	1.42***	1.941	1.16***	1.765	1.53***	2.009	1.73***	1.901	2.08***	2.254
Independent Variables										
Individual-level										
Female (1=Yes)	58.5									
White (1=Yes)	84.6									
Education	12.9	2.763	13.56	2.73	13.12	2.39	11.81	3.43	12.07	2.99
Age	65.49	10.15	65.02	9.83	66.30	10.46	62.54	8.78	63.95	9.71
Coupled Status	66.05%	—	79.02%	—	59.53%	—	62.65%	—	33.2%	—
Medicaid	4.49%	—	1.88%	—	4.33%	—	12.81%	—	18.2%	—
Medicare	48.65%	—	46.56%	—	51.29%	—	41.08%	—	46.1%	—
VA	5.24%	—	6.73%	—	4%	—	9.23%	—	2.7%	—
Private	15.38%	—	14.78%	—	17.71%	—	5.66%	—	6.6%	—
Employer	55.97%	—	59.03%	—	55.65%	—	46.16%	—	44.1%	—
No Insurance	5.6%	—	5.3%	—	4.6%	—	1.19%	—	11.0%	—
Income	10.65	1.23	10.88	1.19	10.59	1.14	10.20	1.48	9.86	1.48
Wealth	11.11	4.74	11.57	4.45	11.38	4.28	8.36	6.34	7.57	6.64
Contextual-level										
Median county income	10.83	.249	10.84	.249	10.84	.247	10.75	.245	10.74	.239
Metro status	76.13%	—	75.53%	—	75.06%	—	84.33%	—	83.62%	—
Gini coefficient	447	34.62	442.37	33.83	442.96	33.39	469.57	34.63	470.75	33.13
2006 Individual weight										
Results based on 1000 stratified bootstrap samples										
***p<.001										

To determine whether there are significant health differences between race and gender groups in the stratified analysis, I used one-way ANOVA with self-rated, physical, and mental health as the dependent variables. I also used post hoc procedures to fully test for group difference. Since the sample sizes for each group are very different and I am not certain that the population variances for each group is equivalent, Field (2009) recommends using Hochberg's GT2 and Games-Howell post hoc test, respectively. The

null-hypothesis for an ANOVA test is that the mean for each health outcome is the same for each group. I also show the appropriate descriptive statistic for each predictor and control variable.

Table 4.1 (above) shows the weighted mean, standard deviation, or percent for all variables. The post-hoc tests for the health outcomes found significant differences in weighted means and percentages for all three outcomes. This means that I reject the null hypothesis and conclude that there are differences between groups in health. The following section describes the dependent and independent variables in more detail.

Dependent variables—Self-rated health

Self-rated health is measured with a 5-point scale that ranges from excellent to poor. Table 4.2 shows the overall and stratified frequency and percentage for each self-rated health response item.

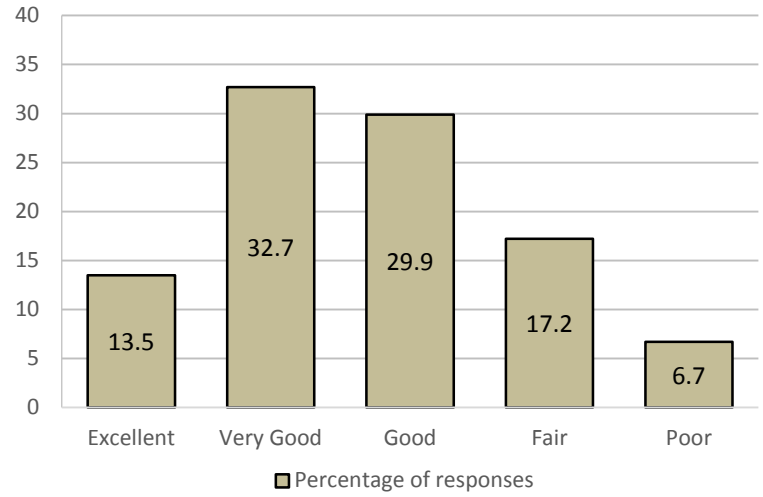
Table 4.2: Frequency and percentage of responses for self-rated health, overall and stratified

	White men (N=5101)		White women (N=6853)		Black men (N=767)		Black women (N=1405)		Overall (N=14126)	
	Freq	%[a]	Freq	%[a]	Freq	%[a]	Freq	%[a]	Freq	%[a]
Excellent	641	14.5	845	14.0	66	9.7	58	5.0	1610	13.5
Very Good	1668	34.4	2254	33.5	175	23.6	280	20.5	4377	32.7
Good	1593	29.3	2130	29.9	239	30.4	489	33.7	4451	29.9
Fair	886	16.0	1165	16.0	208	25.9	422	29.8	2681	17.2
Poor	313	5.8	459	6.6	79	10.4	156	11.0	1007	6.7

[a]2006 individual weighted percentages

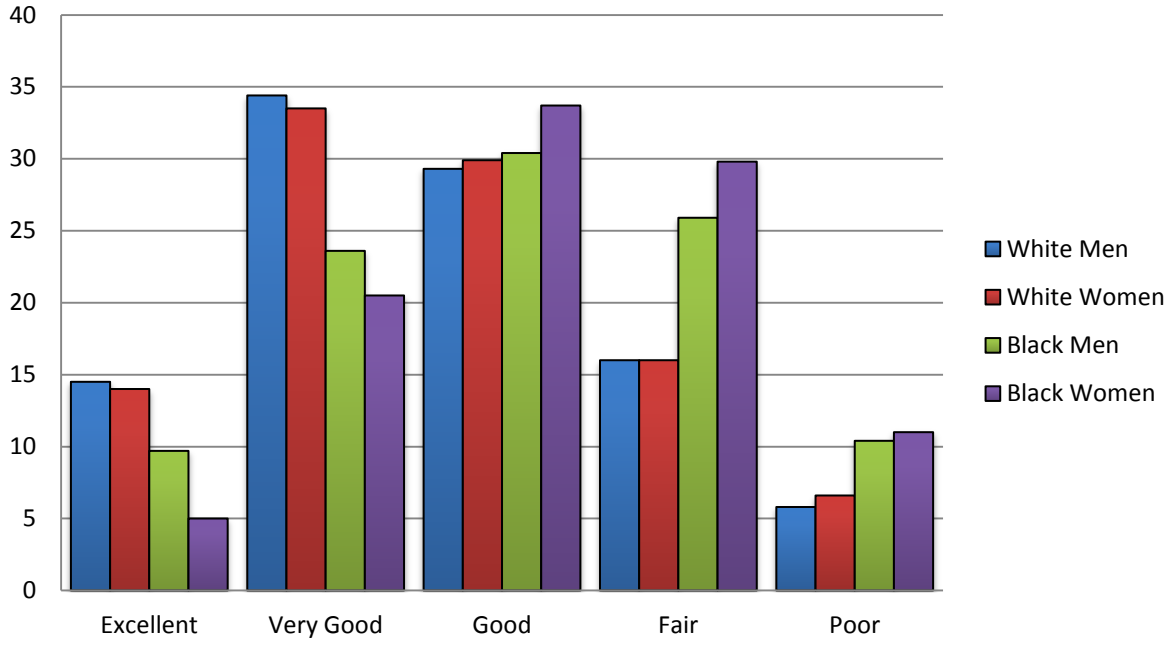
Figures 4.1 and 4.2 show the overall and stratified percentages of the 5 self-rated health response options. While over 60% of people 51 and older in the US report “Very Good” or “Good” health, Whites make up the largest share of these responses. These graphs correspond with the weighted mean difference for self-rated health in Table 4.1 and are the first bit of evidence that stratified modeling may be needed to more fully understand the relationship between income inequality and health.

Figure 4.1: Percentages of frequency of responses for Self-rated health, overall a



[a]2006 individual weighted percentages

Figure 4.2: Percentages of responses for self-rated health, by race and gender group [a]



[a]2006 individual weighted percentages

Dependent variables—Physical Health

Physical health is measured with an index of the 5 most prevalent diseases or conditions that affect middle- and older-aged individuals, according to the US

Department of Health and Human Services Administration on Aging (AOA 2013). Table 4.3 shows the overall and stratified frequency and percentages for each disease or condition.

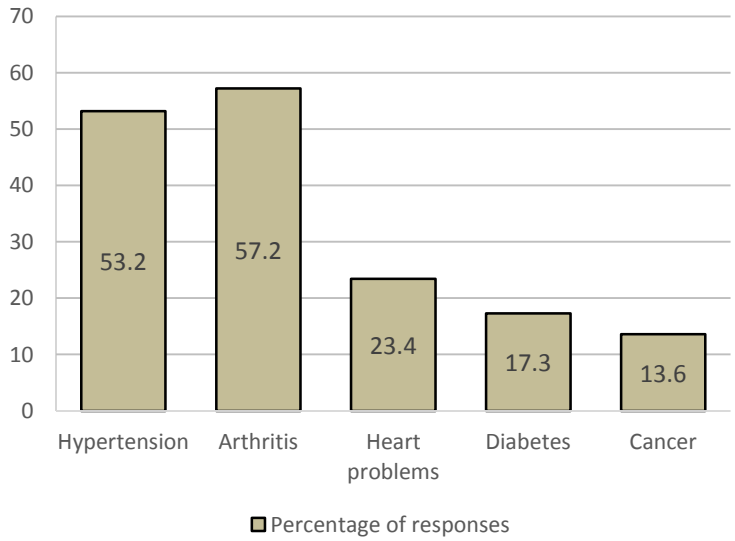
Table 4.3 Frequency and percentages of responses for physical health

	White men (N=5101)		White women (N=6853)		Black men (N=767)		Black women (N=1405)		Total (N=14126)	
	Freq	%[a]	Freq	%[a]	Freq	%[a]	Freq	%[a]	Freq	%[a]
Hypertension	2805	55.0	3850	56.2	524	68.3	1077	76.7	8256	53.2
Arthritis	2806	55.0	4675	68.2	385	50.2	993	70.7	8859	57.2
Heart problems	1649	32.3	1607	23.4	175	22.8	342	24.3	3773	23.4
Diabetes	1028	20.2	1042	15.2	222	28.9	442	31.5	2734	17.3
Cancer	858	16.8	1089	15.9	107	14.0	146	10.4	2200	13.6

[a]**2006 individual weighted percentages**

Figure 4.3 illustrates the overall weighted percentages for each disease or condition. By far, hypertension and arthritis are the most common diseases for those 51 and older, with heart disease, diabetes, and cancer less prevalent.

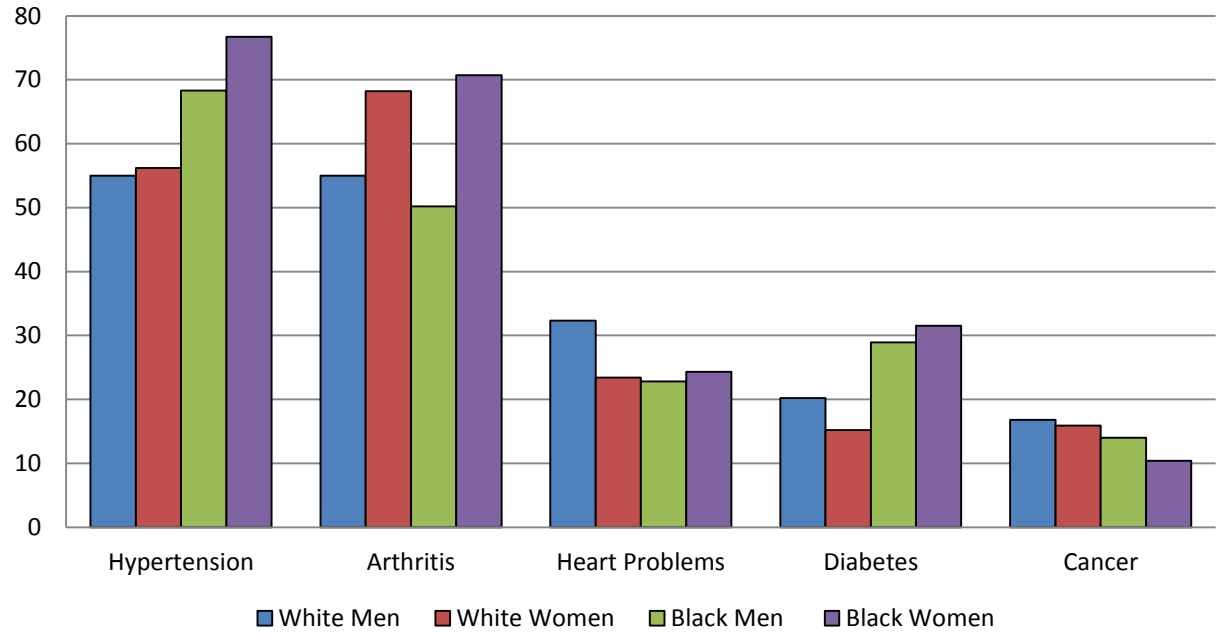
Figure 4.3: Percentage of population 51 and older reporting each disease or condition, overall [a]



[a]**2006 individual weighted percentages**

Figure 4.4 shows how each of these diseases or conditions affects race and gender groups differently.

Figure 4.4: Percentage of population 51 and older reporting each disease or condition, by race and gender group[a]

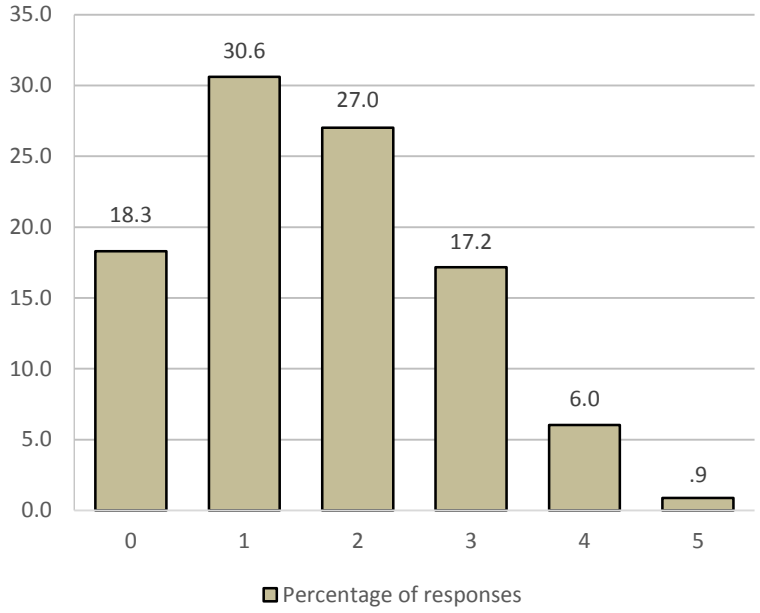


[a]2006 individual weighted percentages

These figures show that middle- and older- aged Blacks report being diagnosed with hypertension and diabetes in greater proportions than similarly aged Whites, with Black women more diagnosed than Black men for both diseases. Far greater shares of women report suffering from arthritis than men, with White and Black women diagnosed in fairly similar proportions. White men represent the largest portion of those diagnosed with heart problems, while White women report higher proportions of cancer diagnoses.

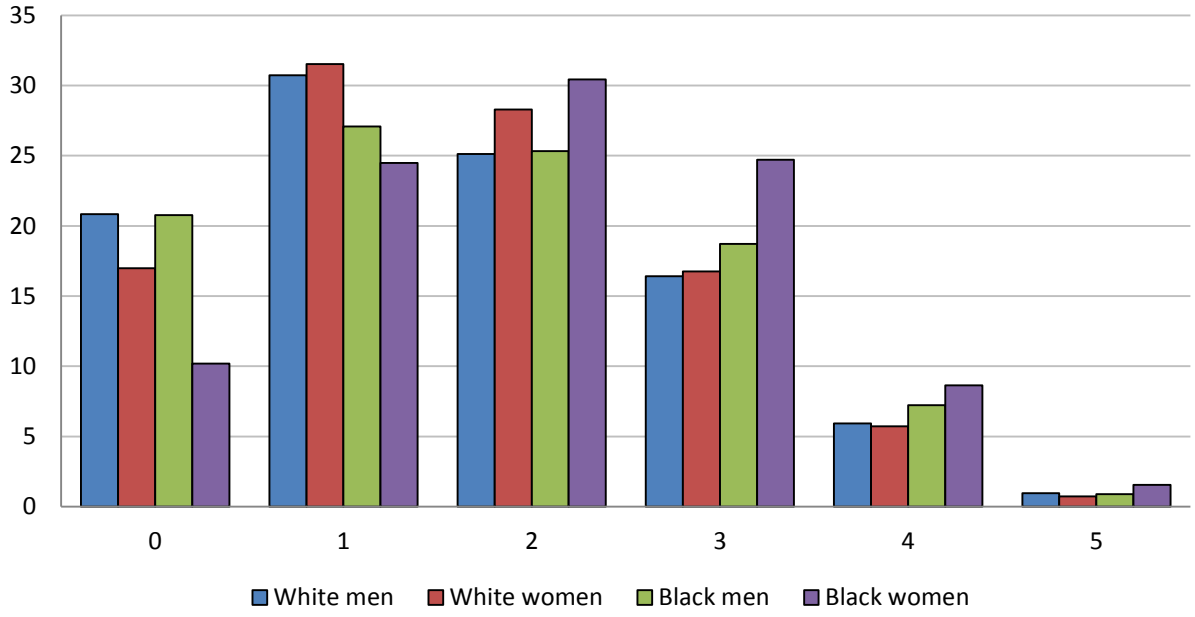
Figure 4.5 is a histogram of the distribution for the physical health index. Just under 50% of the population 51 and older in the US report one or fewer diagnosed diseases or conditions.

Figure 4.5 Percentages of physical health index, overall[a]



[a]2006 individual weighted percentages

Figure 4.6: Percentages of physical health index, by race and gender group[a]



[a]2006 individual weighted percentages

Figure 4.6 breaks down the overall distribution to show how the number of reported diseases differs by race and gender. Men report zero diseases in greater proportions than women. In general, women and Black men have more diseases or conditions than

White men, although the proportion reporting 5 diseases is very similar for all four groups.

Dependent variables—Mental health

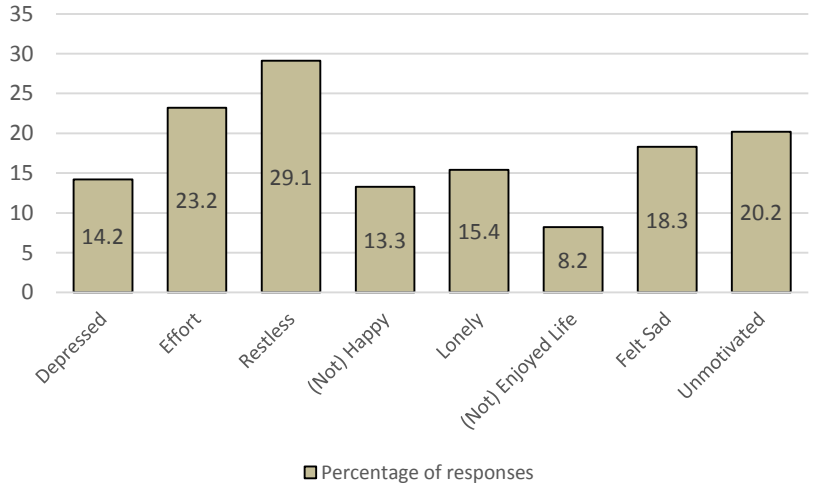
Mental health is measured with the 8-point CES-D scale. Table 4.4 shows the overall and stratified frequencies and percentages for each symptom of depression. The measures labeled “Happy” and “Enjoyed Life” are reverse coded, so individuals reporting these symptoms are actually saying they are not happy and that they do not enjoy life, respectively.

Table 4.4: Frequency and percentages of responses for physical health, overall and stratified

	White men (N=5101)		White women (N=6853)		Black men (N=767)		Black women (N=1405)		Total (N=14126)	
	Freq	%[a]	Freq	%[a]	Freq	%[a]	Freq	%[a]	Freq	%[a]
Depressed	535	11	1010	14.9	157	22.5	342	25.2	2044	14.2
Effort	959	19.4	1517	22.2	356	47.0	568	42.8	3400	23.2
Restless	1203	25	2166	32.4	182	24.7	441	33.1	3992	29.1
Happy[b]	549	12.2	870	13.3	106	16.2	228	18.9	1753	13.3
Lonely	561	11.1	1194	17.2	150	21.2	356	25.9	2261	15.4
Enjoyed Life[b]	310	7.2	592	9.4	35	4.7	85	7.8	1022	8.2
Felt Sad	621	13.2	1460	21.8	125	17.1	351	26.0	2557	18.3
Unmotivated	893	17.0	1543	21.9	157	19.7	386	27.8	2979	20.2

[a]2006 individual weighted percentages
[b]reverse coded

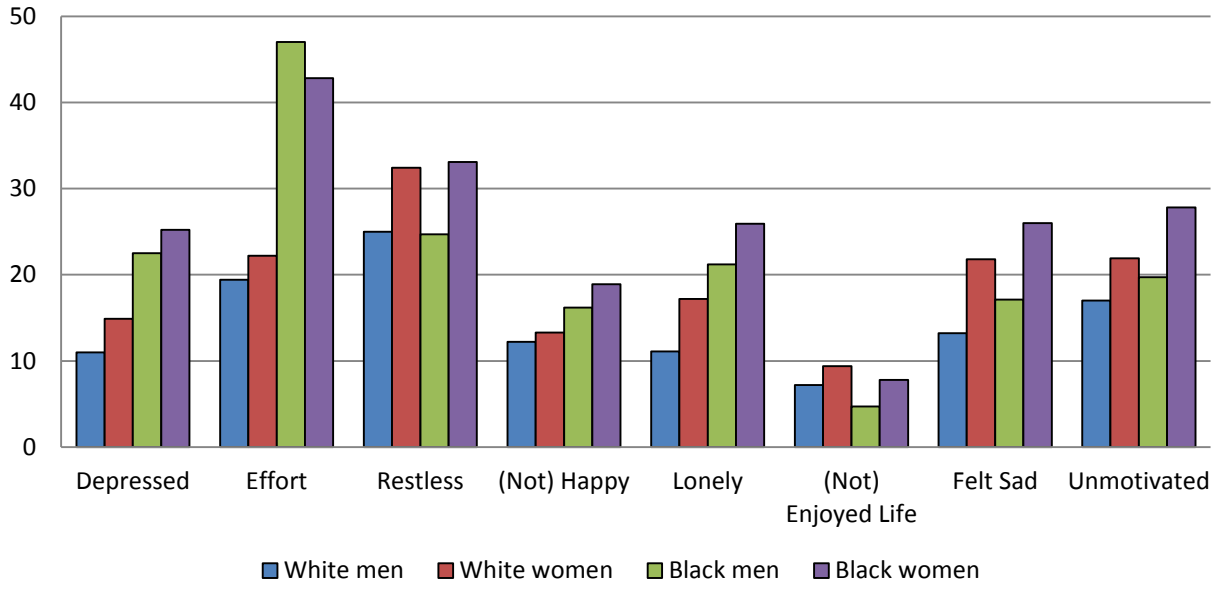
Figure 4.7: Percentage of population 51 and older reporting each response item for mental health, overall [a]



[a]2006 individual weighted percentages

Figures 4.7 (above) and 4.8 (below) show the overall and stratified frequency for each depressive symptom.

Figure 4.8: Percentage of population 51 and older reporting each disease or condition, by race and gender[a]

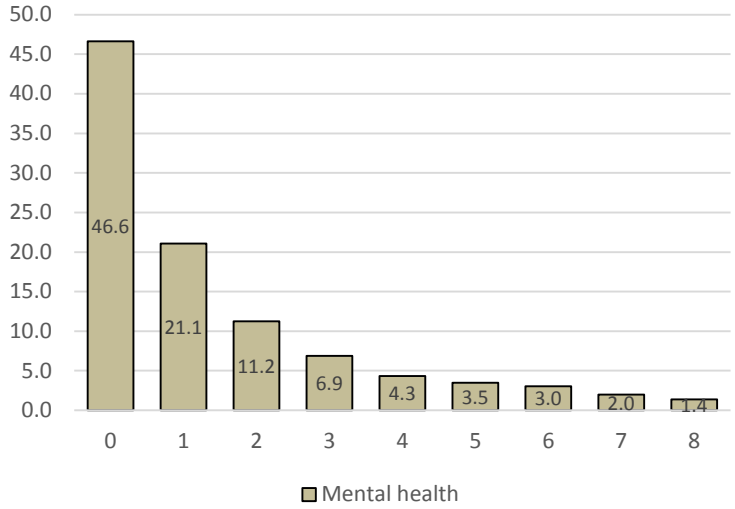


[a]2006 individual weighted percentages

The portion of older Blacks who report that everything in their life is an effort is about twice that of similarly aged whites. Blacks also report being depressed, not being happy, and being lonely in greater proportions than Whites. Women report restlessness, feeling sad, and being unmotivated in greater proportions than men. In general, White men report the fewest symptoms of poor mental health, while Black women rank near the top in every category.

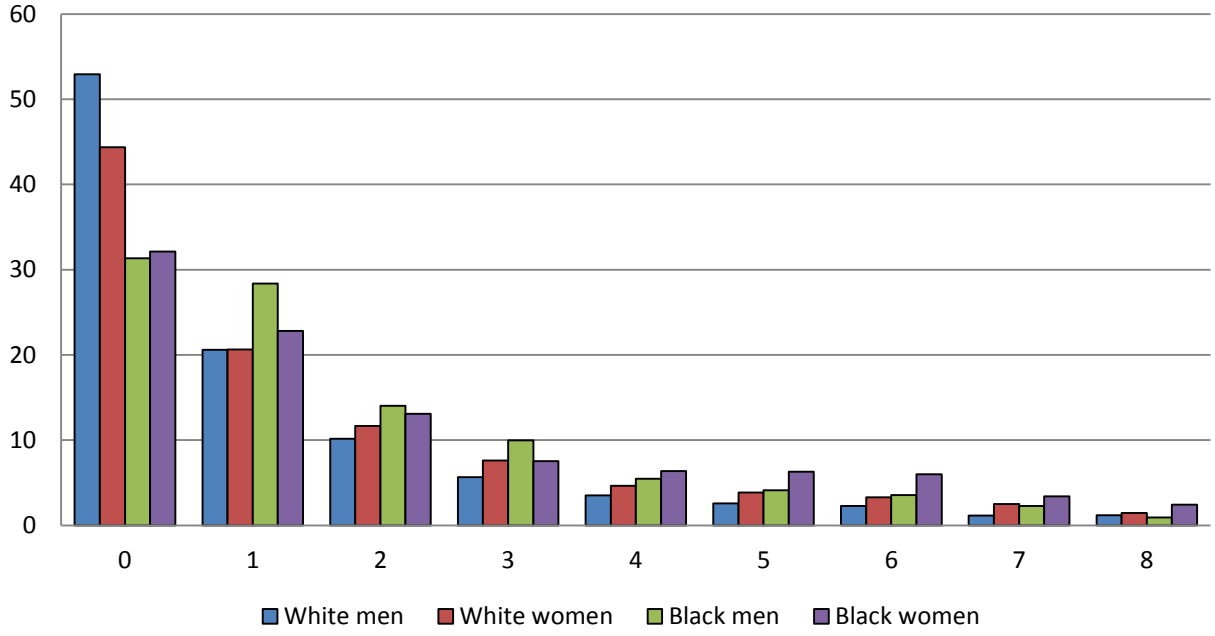
Figure 4.9 illustrates the distribution of the mental health index, while Figure 4.10 is the stratified distribution. Slightly more than 65% of those 51 and older report having one or fewer depressive symptoms, overall, but this percentage reflects White respondents to a greater degree than Black respondents

Figure 4.9: Percentages of each response item for the mental health index, overalla



[a]2006 individual weighted percentages

Figure 4.10: Percentages of each response item for the mental health index, by race and gender[a]



[a]2006 individual weighted percentages

As mentioned in Chapter 4, these last two figures reveal a severely skewed distribution for mental health. In order to assess whether this skew may impact modeling results, I used sensitivity analysis. One technique often used is to transform the skewed variable and run the analysis with both the natural and transformed

variables. A common transformation procedure is to convert scores into their natural logarithm. Since it is impossible to convert zero into a natural logarithm, I first added one point to each respondent's mental health score before conversion. Sensitivity analysis showed that the results of using the logged value for mental health did not change the significance or direction of any variable in all models for mental health. As I am already using a logged value for income and there was no real difference in model outcome between the natural and logged value, for clarity in interpretation I use the natural value for the mental health outcome.

Figure 4.10 shows that over 50% of White men 51 and older report zero symptoms of mental health, compared to about 45% of similarly aged White women. The proportion of White men and White women who report one symptom of mental health is nearly identical, at about 20%. In contrast, only about 30% of Black men and women report zero mental health symptoms. A greater share of Black men than Black women over 50 report one symptom of depression, but the proportion of Black women who report 4 or more symptoms is higher than the other three groups.

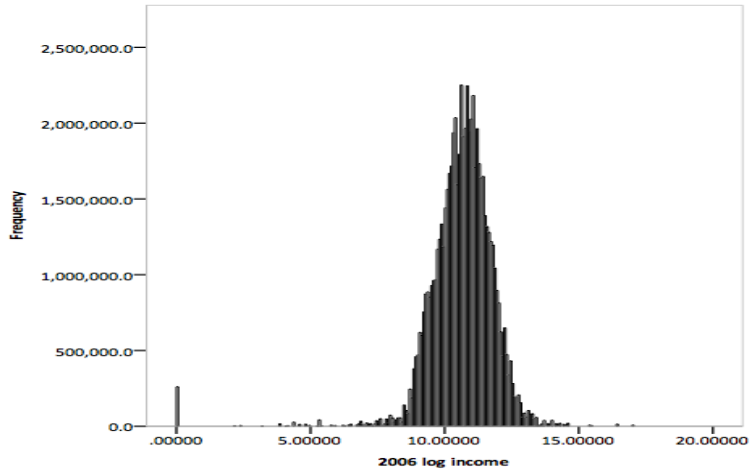
Results section I: Independent variables

In this section, I report the univariate and bivariate descriptive statistics for the independent variables of income and income inequality, as measured by the natural logarithm of individual income and county-level Gini coefficient, respectively.

Income

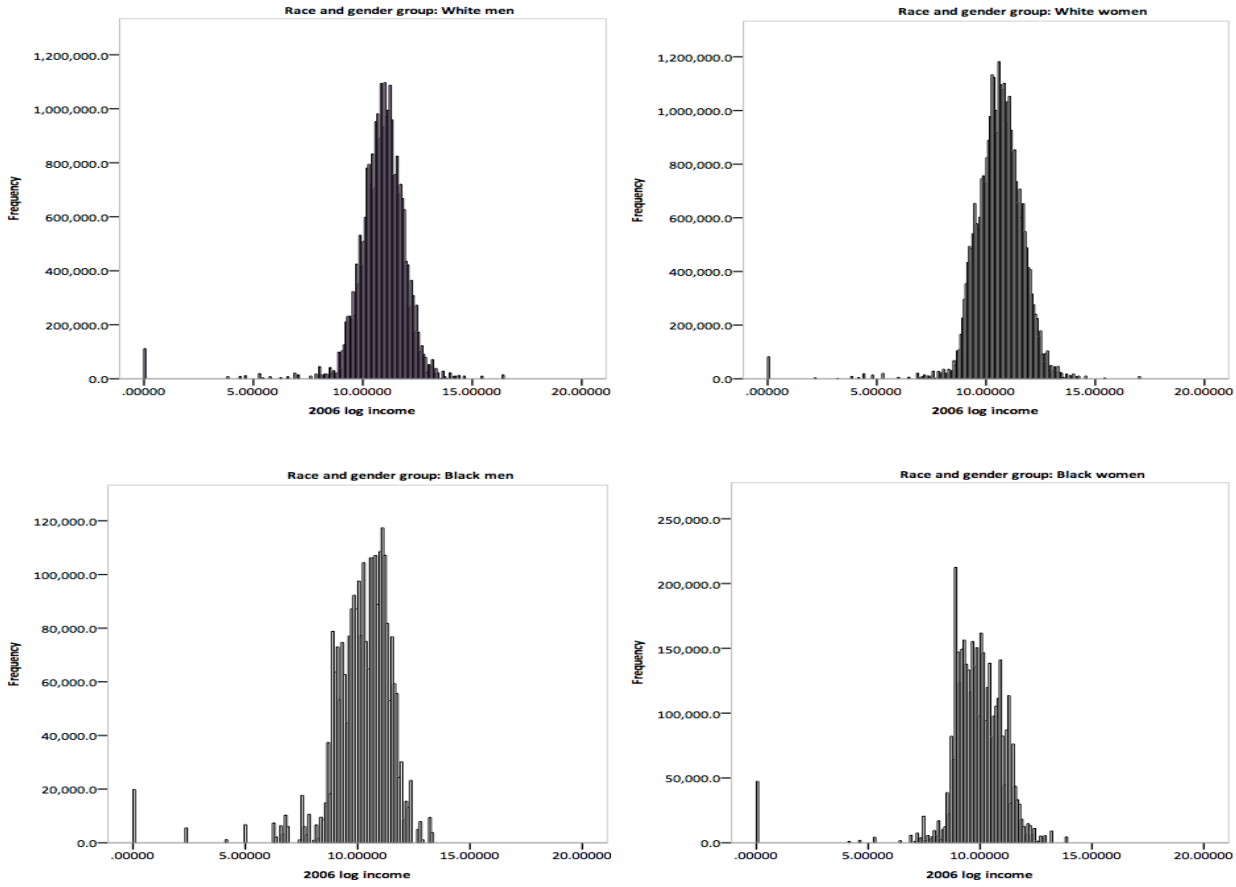
Figure 4.11 is the histogram of the overall distribution of logged income, and Figure 4.12 shows the histograms of the stratified distributions.

Figure 4.11: Histogram of log income, overall[a]



[a]2006 individual weighted values

Figure 4.12 1: Histograms of log income, by race and gender group[a]



[a]2006 individual weighted values

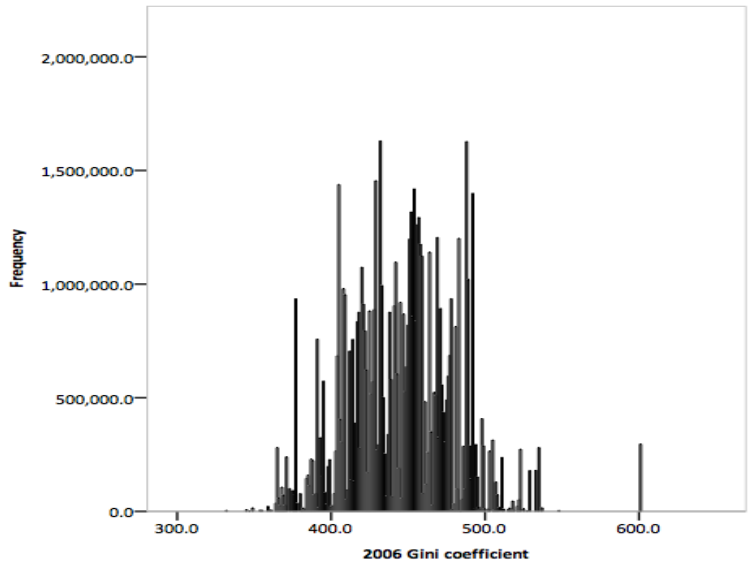
These histograms show that the distribution of income is much more normal for middle- and older aged Whites than Blacks. In addition, White men and women also have much

higher mean log income than Blacks, especially Black women. The share of individuals with zero income is much higher for Blacks than for Whites, as well.

Gini coefficient

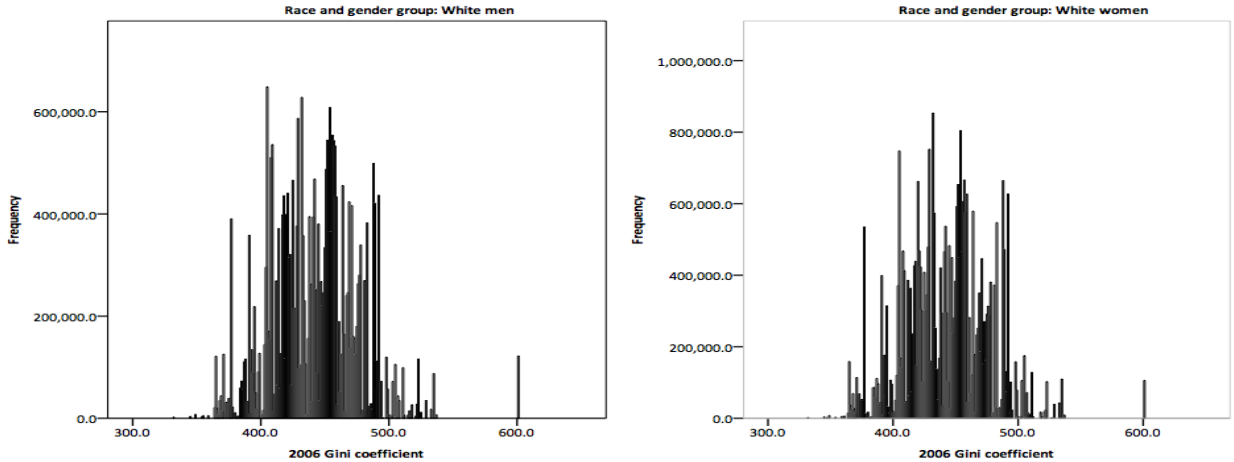
Figure 4.13 shows the distribution of the overall distribution of the Gini coefficient, and Figure 4.14 shows the stratified distributions. These figures show that the distribution for Whites is relatively normal compared to Blacks.

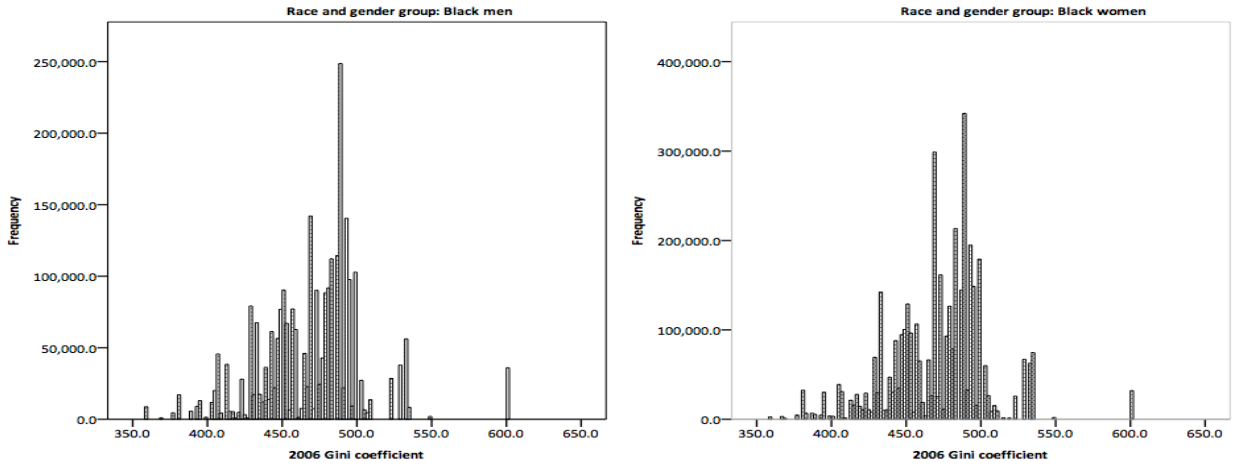
Figure 4.13: Distribution of Gini coefficient, overall [a]



[a]2006 individual weighted values

Figure 4.14: Histogram of Gini coefficient, by gender and race group[a]





[a]2006 individual weighted values

County Profiles

What do equal and unequal counties look like? In this section I profile each type of county to highlight the similarities and differences between them. Table 4.5 shows weighted overall descriptive statistics for the population of community dwelling persons 51 and older. They are also stratified by Gini coefficient tertile. Each group is comprised of roughly 1/3rd of the counties and represents counties with low, medium, and high inequality.

Table 4.5: Weighted descriptive statistics, overall and stratified by Gini coefficient

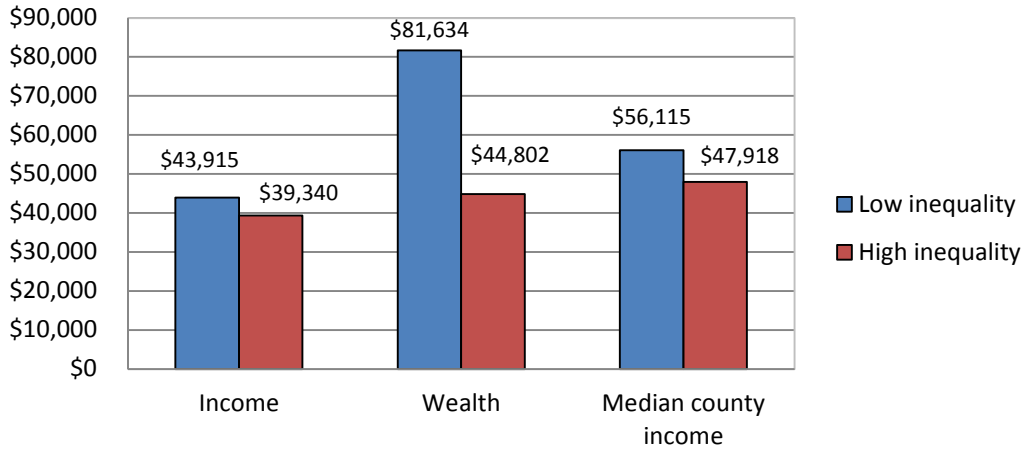
	Total Sample		Low inequality		Medium inequality		High inequality	
	N=14126		N=4568		N=4601		N=4957	
	Mean/		Mean/		Mean/		Mean/	
	Percent	SD	Percent	SD	Percent	SD	Percent	SD
Dependent Variables								
Self-rated health (1-5)	2.71	1.11	2.67	1.08	2.70	1.10	2.76	1.14
Physical health (0-5)	1.65	1.19	1.62	1.19	1.68	1.18	1.64	1.18
Mental health (0-8)	1.42	1.94	1.34	1.89	1.37	1.91	1.55	2.02
Independent Variables								
Individual-level								
Female (1=Yes)	55.2%	—	53.9%	—	55.4%	—	56.4%	—
Black (1=Yes)	9.9%	—	3.2%	—	7.4%	—	19.6%	—
Education	13.19	2.66	13.18	2.50	13.19	2.60	13.19	2.87
Age	65.5	10.15	64.8	10.13	66.5	10.21	65.2	10.02
Coupled Status	66.1%	—	70.2%	—	66.3%	—	61.3%	—
Medicaid	4.5%	—	2.9%	—	4.5%	—	6.2%	—
Medicare	48.6%	—	45.1%	—	53.1%	—	48.1%	—
VA	5.2%	—	5.6%	—	4.7%	—	5.5%	—
Private	15.4%	—	17.8	—	15.4%	—	12.8%	—
Employer	56%	—	59.1%	—	54.5%	—	54.0%	—
No Insurance	5.6%	—	4.8%	—	4.9%	—	7%	—
Income*	10.65	1.23	10.69	1.24	10.67	1.15	10.58	1.27
Wealth*	11.11	4.74	11.31	4.47	11.31	4.47	10.71	5.24
County-level								
Metropolitan status			63.5%	—	82.0%	—	84.0%	—
Med co. income			$56,115	$14,492	$52,273	$13,531	$47,918	$12,086
Gini coefficient			409.4 332-431	16.84	446.71 432--458	8.40	483.10 459-601	21.45

[a]2006 individual weights

* logged income and wealth

Figures 4.15-4.19 illustrate some of the differences between middle- and older aged residents of the US who live in low and high inequality counties.

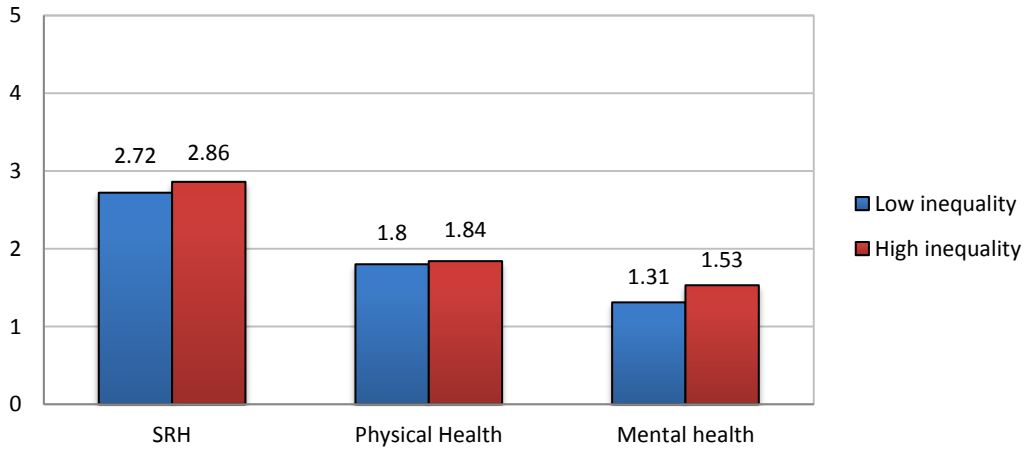
Figure 4.15: Mean income, wealth, and median county income for low and high inequality counties



Mean income and wealth are higher in counties with low inequality compared to counties with high inequality. Middle- and older-aged individuals living in low inequality counties earn $4,574 more income and have $36,832 more wealth than similarly aged individuals living in high inequality counties. Median county income is also greater in low inequality counties, falling by $8,197 in high inequality counties.

Figures 4.16, 4.17, and 4.18 show that health is affected by inequality, too.

Figure 4.16: Mean of self-rated, physical, and mental health for low and high inequality counties



Self-rated and physical health are moderately worse in high inequality counties, and mental health is markedly similar. Low inequality counties have lower percentages of respondents with diabetes, hypertension, and cancer but higher percentages with heart problems and arthritis. All 8 mental health indicators are noticeably higher in more unequal counties than in more equal counties.

Figure 4.17: Percent reporting each physical disease or condition for low and high inequality counties

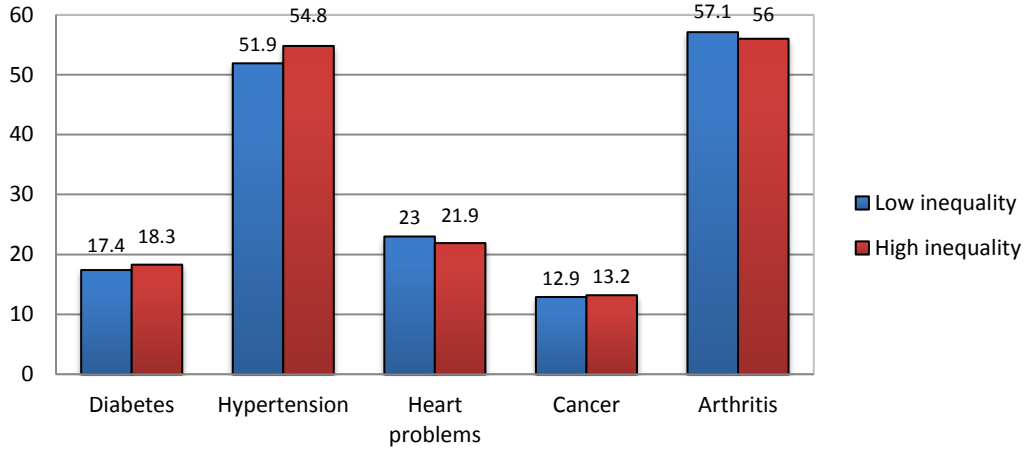


Figure 4.18: Percent reporting each mental health indicator for low and high inequality counties

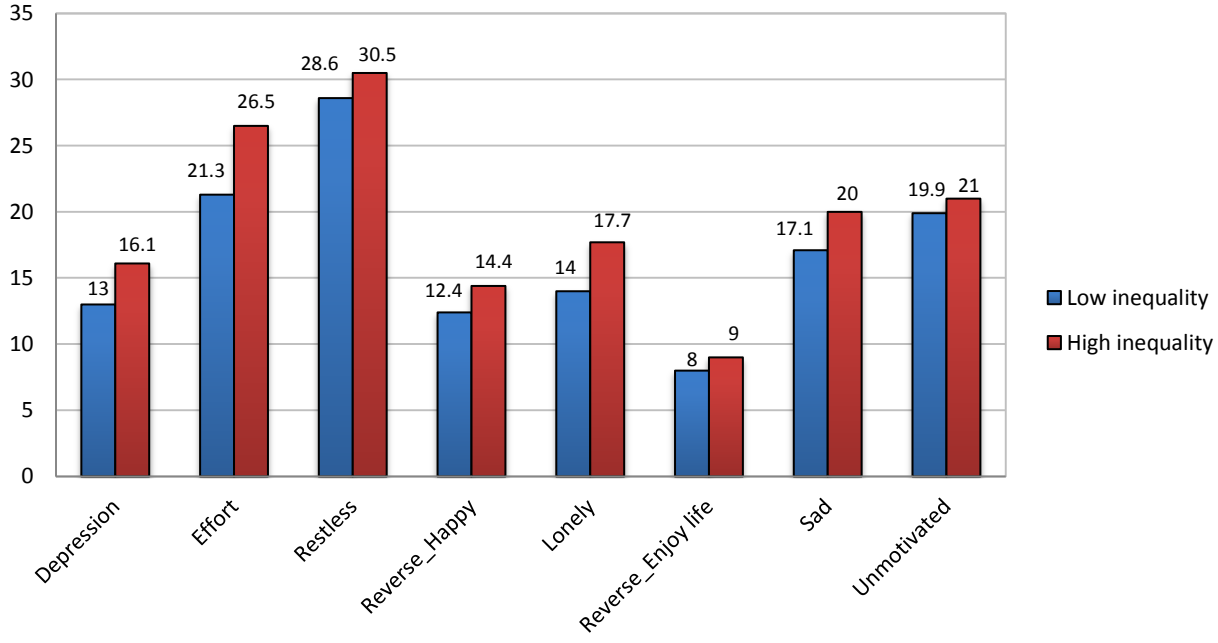
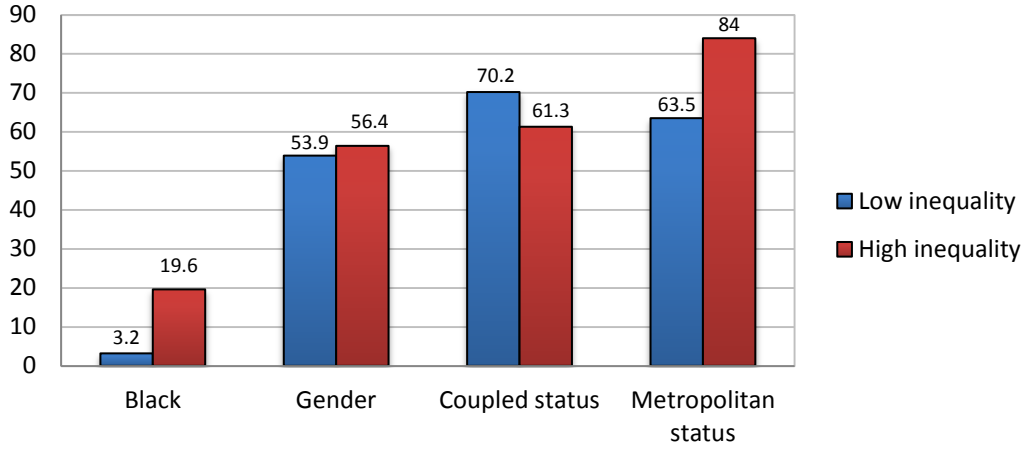


Figure 4.19: Percentages of select demographic characteristics for low and high inequality counties



Counties with high inequality have lower percentages of married couples and are also more likely to be located in metropolitan areas than rural ones. Unequal counties have a much larger percentage of Blacks and slightly higher percentages of women.

Social group profiles

In addition to outlining how inequality affects the county-level, this section profiles the complex ways it shapes and uniquely affects the lives of individuals. Tables similar to 4.5 (above) showing the weighted overall and stratified descriptive statistics for each social group are included in Appendix B. The next three figures illustrate these tables and show the income, wealth and median county income of each group.

Figure 4.20: Mean income for each social group for low and high inequality counties

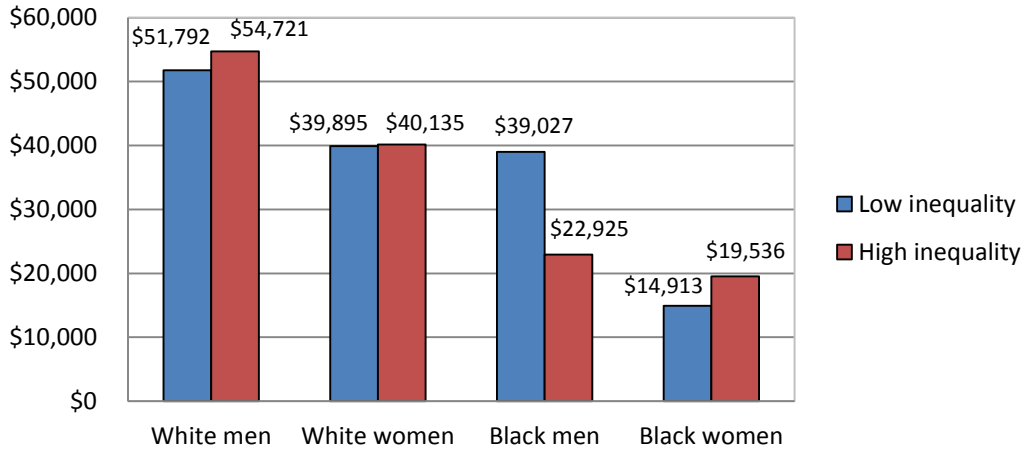


Figure 4.20 shows that compared to low inequality counties, income in high inequality counties increases for Whites and Black women while plummeting for Black men. A slightly similar pattern is seen in Figure 4.21, as wealth in high inequality counties increases for Whites. Here, Black women join Black men in seeing their wealth decrease in high inequality counties. Black women's wealth loss, though, is miniscule compared to the considerable decrease in Black men's wealth.

Figure 4.21: Mean wealth for each social group for low and high inequality counties

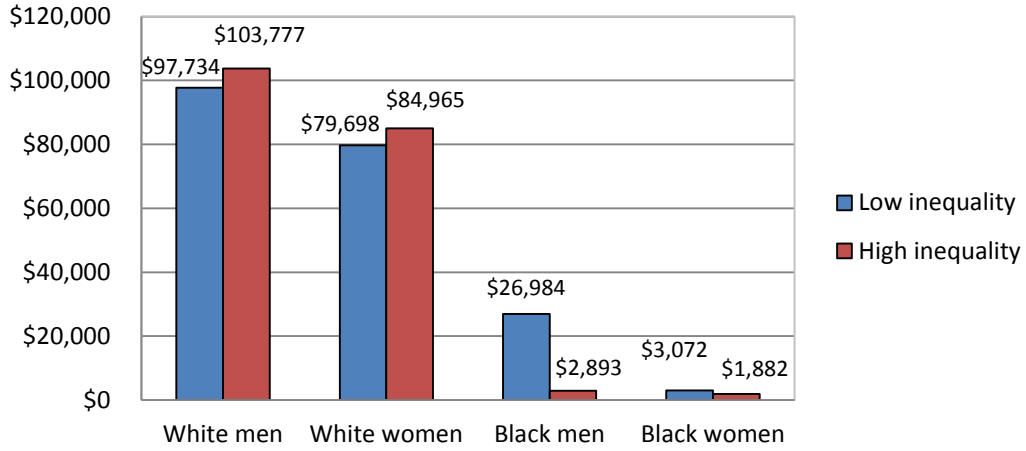
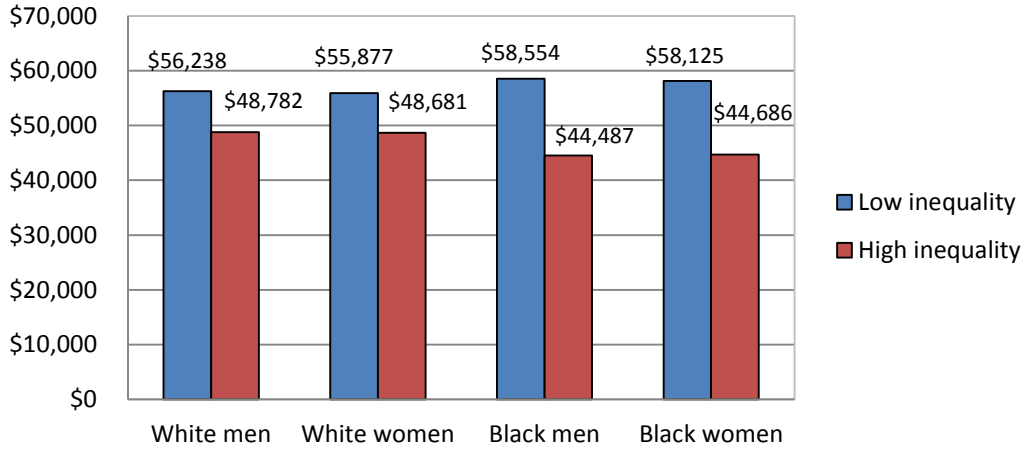


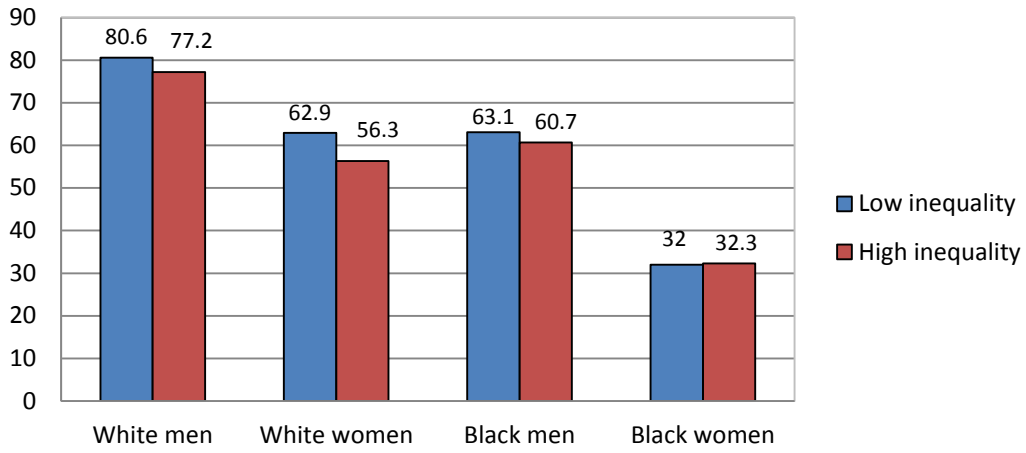
Figure 4.22: Median county income for each social group for low and high inequality counties



Median county income for all groups falls in highly unequal counties compared to more equal counties, as detailed in Figure 4.22. What is also interesting in this figure is that in low inequality counties, Black median county income is actually higher than for Whites,

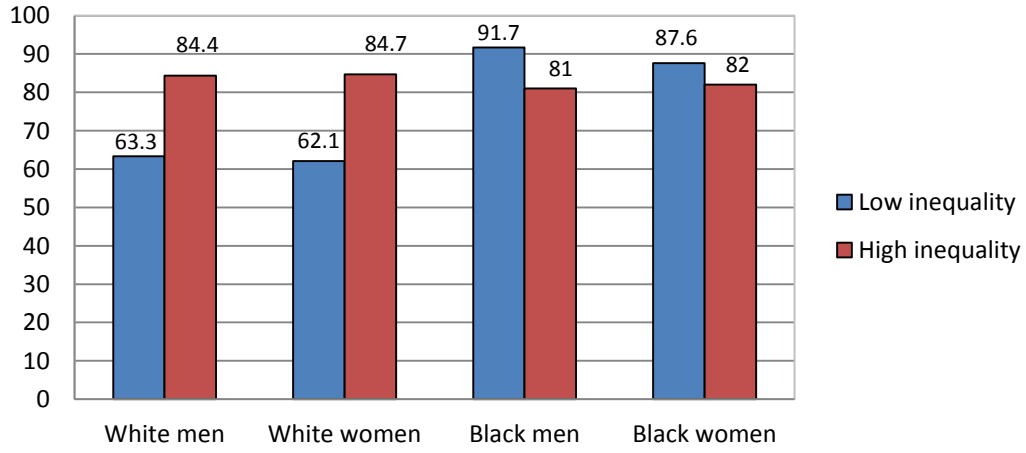
but then falls more sharply than White's does in high inequality counties.

Figure 4.23: Percentage of coupled individuals for each social group for low and high inequality counties



High inequality counties have smaller percentages of married couples than counties with low inequality (Figure 4.23). The effect is the greatest for White women while affecting Black and White men about equally. The percentage of Black women who are married in low and high inequality counties are virtually the same, although their much lower likelihood of being coupled in either type of county is remarkable.

Figure 4.24: Metropolitan status for each social group for low and high inequality counties



Whites who live in counties with low inequality are less likely to live in metropolitan areas compared to Blacks living in counties with similar inequality. However, this status

is reversed for Whites and Blacks living in high inequality counties, as fewer percentages of Blacks in this type of county live in metropolitan areas than Whites (Figure 4.24).

The last four figures in this section (4.25-4.28) detail the health of each social group living in low and high inequality counties. SRH decreases slightly for all four groups in high inequality counties when compared to low inequality counties (higher numbers represent worse health). Physical health actually increases for all groups as the mean number of physical diseases or conditions is lower in high inequality counties.

Figure 4.25: Mean health for White men living in low and high inequality counties

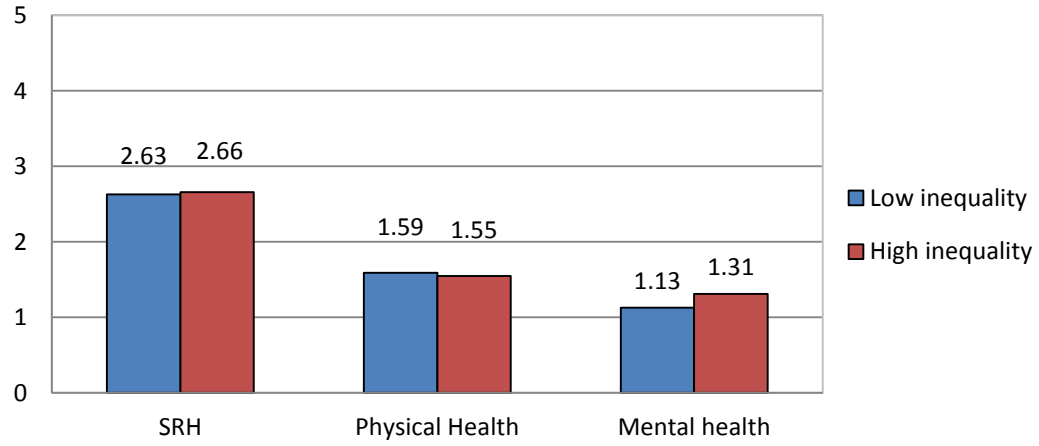


Figure 4.26: Mean health for White women living in low and high inequality counties

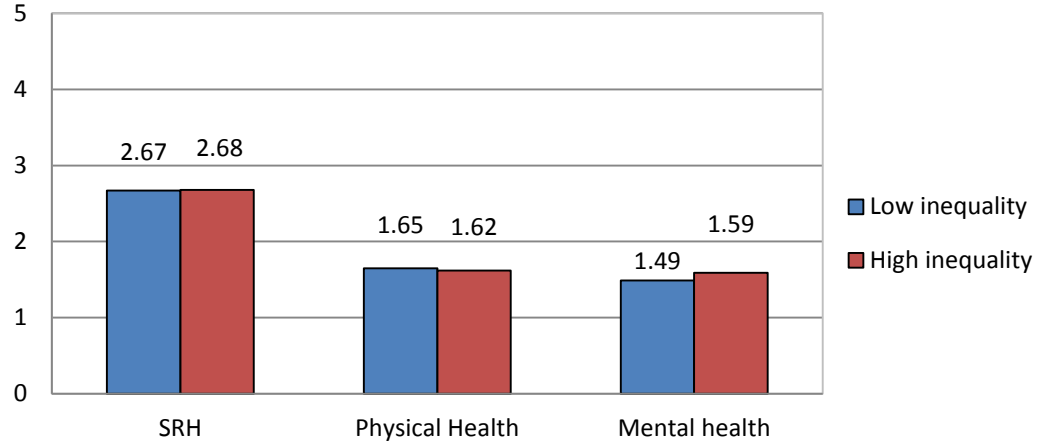


Figure 4.27: Mean health for Black men living in low and high inequality counties

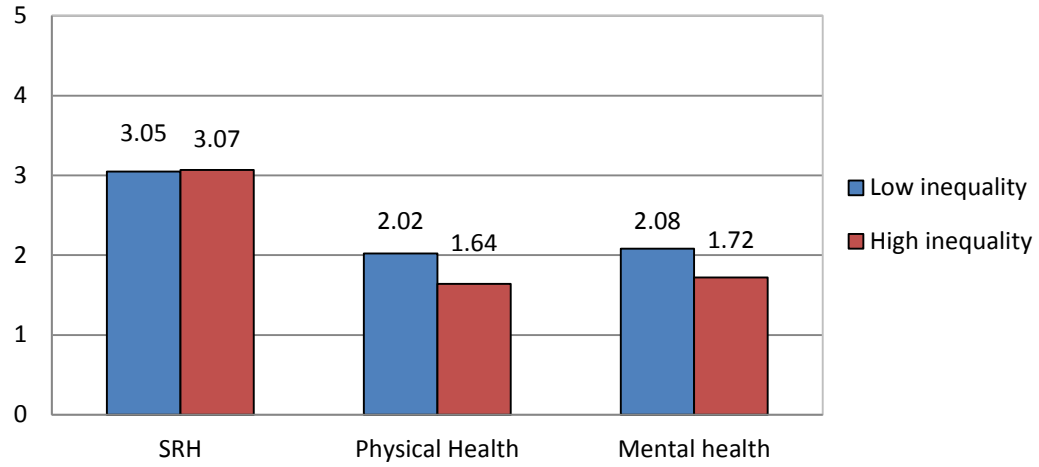
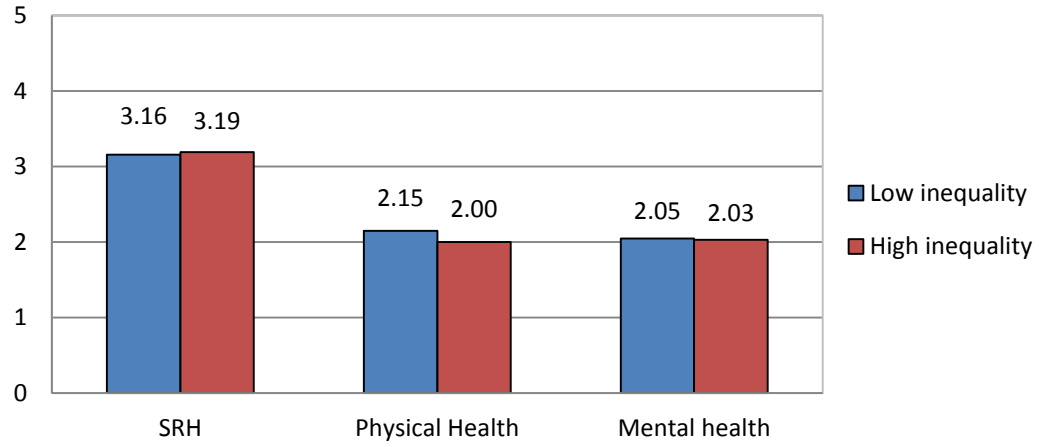


Figure 4.28: Mean health for Black women living in low and high inequality counties



The groups diverge, however, concerning mental health, where it is worse in high inequality counties for Whites but not for Blacks. In particular, Black men living in high inequality counties report far fewer symptoms of poor mental health than those living in counties with low inequality.

Summary of results section I

These descriptive statistics show that health varies substantially by race and gender group. Such variation suggests that concentrating only on the overall relationship between income inequality and health may not present an accurate picture of this problem.

Results section II: Model adequacy

In this section, I describe the three steps I undertook to assess the adequacy of the overall and stratified models used in the analyses of income inequality and health. In step 1, I test the underlying theory that health does in fact vary across geographic context with the likelihood ratio test. In Step 2, I use the intra-class correlation to determine if the use of multi-level modeling was the appropriate statistical technique to use for this analysis. And in Step 3, I assess the models for goodness of fit to see how well they fit the data. Each of these tests will be discussed in more detail below.

Model adequacy: Step 1—The likelihood ratio test

The underlying assumption of this research depends on whether the health of an individual is, in part, dependent on one's economic context. Therefore, it is vital to assess whether individual health does, in fact, vary as hypothesized across context. To test this theory I use the likelihood ratio test, which compares the -2 Log Likelihood (-2LL) statistic of the single- and multi-level null models for each health outcome. Null models are models with no predictor variables so the intercepts reported in them are the average of each health outcome. In the single-level null model, the intercept is fixed, or held constant, and in the multi-level null model it is allowed to vary randomly across counties.[1] The null hypothesis for the likelihood ratio test is that the difference in health variability between the single-level fixed and multi-level random null models is zero.

Tables 4.5-4.9 show the results of the likelihood ratio test for all three outcomes, for the overall and stratified models. The -2LL column in each table shows the value of the statistic for the individual-level fixed and county-level random intercept null models,

[1] Although this multi-level model may not "technically" be a null model since it does contain the county predictor of the intercept, I am describing it as such in this research.

while the other two columns show the degrees of freedom for each model, and the difference in the -2LL statistic between the models. As shown in the tables, the -2LL statistic in all random models is smaller than that in the fixed models for each outcome. Since the -2LL statistic assesses how many unexplained observations there are after a model has been fit, smaller -2LL values are one indication of better model fit (Field 2009). To test whether these differences in value are statistically significant, I use a chi-square ($\chi 2$) difference test. A $\chi 2$ difference test is meaningful when models are nested, such as these are. Nested models simply mean that the results of one of the models could be obtained by fixing one (or more, if applicable) of the parameters of the other model. Fixing a parameter in a model reduces the degrees of freedom (*df*) in that model because one less parameter is allowed to vary. In the case of this research, this means the intercept (average of each health outcome) in the single-level model is held constant (fixed). Consequently, as shown in each table, the fixed intercept models have one less *df* than the random intercept models.

Table 4.6: Log likelihood ratio tests for Physical, Self-Rated, and Mental health, overall

Null models	-2LL	df	**Δ**
Self-rated health			
Fixed intercept	2021.01×10^5	2	
Random intercept	1930.53×10^5	3	90.49×10^5
Physical health			
Fixed intercept	2114.88×10^5	2	
Random intercept	2034.69×10^5	3	80.19×10^5
Mental health			
Fixed intercept	2771.00×10^5	2	
Random intercept	2701.49×10^5	3	69.51×10^5

Table 4.7: Log likelihood ratio tests for Physical, Self-Rated, and Mental health, White men

Null models	-2LL	df	**Δ**
Self-rated health			
Fixed intercept	818.23×10^5	2	
Random intercept	758.31×10^5	3	59.93×10^5
Physical health			
Fixed intercept	874.12×10^5	2	
Random intercept	817.12×10^5	3	57.00×10^5
Mental health			
Fixed intercept	1080.39×10^5	2	
Random intercept	1036.30×10^5	3	44.08×10^5

Table 4.8: Log likelihood ratio tests for Physical, Self-Rated, and Mental health, White women

Null models	-2LL	df	**Δ**
Self-rated health			
Fixed intercept	993.45×10^5	2	
Random intercept	933.63×10^5	3	59.82×10^5
Physical health			
Fixed intercept	1024.37×10^5	2	
Random intercept	966.92×10^5	3	57.45×10^5
Mental health			
Fixed intercept	1387.42×10^5	2	
Random intercept	1333.30×10^5	3	54.12×10^5

Table 4.9: Log likelihood ratio tests for Physical, Self-Rated, and Mental health, Black men

Null models	-2LL	df	**Δ**
Self-rated health			
Fixed intercept	81.45×10^5	2	
Random intercept	72.31×10^5	3	9.13×10^5
Physical health			
Fixed intercept	86.15×10^5	2	
Random intercept	77.75×10^5	3	8.40×10^5
Mental health			
Fixed intercept	108.40×10^5	2	
Random intercept	99.09×10^5	3	9.31×10^5

Table 4.10: Log likelihood ratio tests for Physical, Self-Rated, and Mental health, Black women

Null models	-2LL	df	**Δ**
Self-rated health			
Fixed intercept	115.72×10^5	2	
Random intercept	107.09×10^5	3	8.63×10^5
Physical health			
Fixed intercept	124.89×10^5	2	
Random intercept	117.68×10^5	3	7.21×10^5
Mental health			
Fixed intercept	176.22×10^5	2	
Random intercept	168.01×10^5	3	8.21×10^5

To compute a χ2 difference test in this context, I noted the difference in the -2LL and (*df*) between the random and fixed null models. I then referenced a χ2 table to find that the differences between the -2LL values are statistically significant for a χ2 distribution with a single degree of freedom. This means that I reject the null hypothesis that there is no difference and conclude that self-rated, physical, and mental health does vary significantly across counties in both the overall and stratified models.

Model adequacy: Step 2—The intra-class correlation

Having established that health does indeed vary across geographic context, I next want to know, by how much? The answer to this question will determine the choice of statistical technique to use in this research. In other words, is single-level (i.e. OLS) regression sufficient to analyze these geographic differences or are multi-level regression modeling techniques more appropriate? The data in this study are hierarchically organized, as some variables are measured on the contextual level (i.e. the value is the same for everyone living in a given county) and others are measured on the individual level (i.e. values will vary by person). While hierarchical data does not automatically preclude the use of OLS regression, data of this nature must influence the choice of methods.

The chief problem with hierarchal data is that it introduces the possibility of dependency into an analysis (Allison 2009). Dependency is a major violation of a key assumption of OLS regression, in that the residuals will be correlated instead of being independent. A residual is the difference between the observed and expected data points for a variable, and their numbers represent how closely a theorized statistical model matches the sample data. Independent residual values mean that a model more

closely matches the data, which then allows generalization of findings beyond this representative sample to the general US population 51 and older. If the relationships in the sample, though, are dependent on characteristics of cases or variables unique to this particular sample (such as where people live), the use of OLS regression techniques may result in spurious general inferences about those over the age of 50. Since multi-level modeling accounts for this violation of statistical assumptions, MLM would be an appropriate choice to use if dependency existed in the sample. To test for evidence of dependency in this data, I calculated the intraclass correlation (ICC).

The ICC is the ratio of total variation in an outcome that can be attributed to the two levels of measurement for the predictor variable. Here, this means how much of the variability in individual health depends on where one lives. If the majority of variability in health is due to within county differences, then the ICC will be small. This means that the people who live in a particular county are highly dissimilar to each other and any differences noted in health may likely be due to this dissimilarity and not to their county of residence. If this was the case in this research, OLS regression techniques could be justified, since dependency would not be an issue. On the other hand, if the majority of variability in health is, in fact, due to between county differences, then the ICC would be high. This observation would indicate that the people living in a given county are relatively similar to each other, so most of the variability noted in health likely depends on the county where they reside. MLM, then, should be the statistical technique used.

The ICC is calculated using Formula 4.1, with values from the multi-level null random model (the model where the intercept is allowed to vary with no predictor variables):

$$\frac{var(\beta)}{var(\beta)+var(\alpha)} \qquad \text{(Formula 4.1)}$$

where var(β) is the amount of within county variation in each model and var(α) is the amount of between county variation. Tables 4.10-4.14 show the results of the overall and stratified ICC for each health outcome.

Table 4.11: Intraclass Correlation for Physical, Self-Rated, and Mental health, overall

	Between county variation	Within county variation	ICC
Self-rated health	1.066	0.718	0.402
Physical health	1.2466	0.718	0.366
Mental health	3.395	2.125	0.385

Table 4.12: Intraclass Correlation for Physical, Self-Rated, and Mental health, White men

	Between county variation	Within county variation	ICC
Self-rated health	0.953	0.846	0.470
Physical health	1.183	0.912	0.435
Mental health	2.629	1.730	0.397

Table 4.13: Intraclass Correlation for Physical, Self-Rated, and Mental health, White women

	Between county variation	Within county variation	ICC
Self-rated health	1.010	0.813	0.446
Physical health	1.118	0.805	0.419
Mental health	3.420	2.694	0.441

Table 4.14: Intraclass Correlation for Physical, Self-Rated, and Mental health, Black men

	Between county variation	Within county variation	ICC
Self-rated health	0.916	0.719	0.440
Physical health	1.126	1.077	0.489
Mental health	2.536	2.287	0.475

Table 4.15: Intraclass Correlation for Physical, Self-Rated, and Mental health, Black women

	Between county variation	Within county variation	ICC
Self-rated health	0.882	0.658	0.428
Physical health	1.153	0.810	0.413
Mental health	4.126	3.021	0.427

As the tables show, between about 37%-49% of variability in health is associated with the county of residence. Such high values suggest that the residuals are related. In other words, health may partially depend on the county in which an individual lives.

Together with the hierarchical structure of the data, this result is sufficient evidence to conclude that multi-level modeling was the appropriate tool to use in this analysis.

Model adequacy: Step 3—Model comparison

The third step in assessing model adequacy also uses the -2LL value. As mentioned in Step 1 above, low -2LL values are an indication of good model fit, which is a way to judge how closely the models fit the data. However, there is no way to independently evaluate log-likelihood statistics, so I used model comparison. For this assessment of model fit, I used the null random model for each outcome as the baseline and compared its -2LL value to that in Model 2 where the individual-level demographic variables are added, then to the value in Model 3 where the individual-level economic variables are added, and finally to the -2LL value in Model 4 where the contextual-level variables are added. As the models get increasingly more complex, the criterion for better model fit is assessed by the smaller-is-better principle.

Tables 4.15-4.19 summarize the -2LL comparison of the overall and stratified models used to predict the relationship between income inequality and physical, self-rated, and mental health. The first column in these tables indicates which health outcome and model was assessed. The -2LL column shows the value of the Log Likelihood statistic for that model. The last column shows the change in the -2LL statistic between the simpler and more complex models.

Table 4.16: Comparison of Overall MLM predicting the relationship between income inequality and health

	-2LL	**Δ**
Physical health		
Model 1	203469032	
Model 2	193774770	9694262
Model 3	193322187	452583
Model 4	193322184	3
Self-rated health		
Model 1	193052898	
Model 2	184381249	8671649
Model 3	182420076	1961173
Model 4	182420073	3
Mental health		
Model 1	270148873	
Model 2	264619351	5529522
Model 3	263395679	1223672
Model 4	263395678	1

Model 1=Baseline (null model); Model 2=Individual-level predictors and control variables;
Model 3=Individual-level economic variables; Model 4=County-level predictors and control variables.
Criterion for better model fit is assessed by the smaller-is-better principle.

Table 4.17: Comparison of MLM predicting the relationship between income inequality, White men

	-2LL	**Δ**
Physical health		
Model 1	81711865	
Model 2	77417008	4294857
Model 3	77305236	111772
Model 4	77305224	11
Model 5		
Self-rated health		
Model 1	75830531	
Model 2	72606514	3224017
Model 3	71972109	634405
Model 4	71972108	1
Model 5	71836890	
Mental health		
Model 1	103630186	
Model 2	101644517	1985668
Model 3	101211150	433367
Model 4	101211143	7
Model 5		

Model 1=Baseline (null model); Model 2=Individual-level predictors and control variables;
Model 3=Individual-level economic variables; Model 4=County–level predictors and control variables.
Criterion for better model fit is assessed by the smaller-is-better principle.

Table 4.18: Comparison of MLM predicting the relationship between income inequality, White women

	-2Log Likelihood	**Δ**
Physical health		
Model 1	96692353	
Model 2	91738294	4954059
Model 3	91471986	266308
Model 4	91471985	1
Self-rated health		
Model 1	93362671	
Model 2	89178092	4184579
Model 3	88233395	944697
Model 4	88233391	4
Mental health		
Model 1	133330151	
Model 2	131367141	1963010
Model 3	130698054	669087
Model 4	130698052	2

Model 1=Baseline (null model); Model 2=Individual-level predictors and control variables;
Model 3=Individual-level economic variables; Model 4=County–level predictors and control variables.
Criterion for better model fit is assessed by the smaller-is-better principle.

Table 4.19: Comparison of Multilevel Models predicting the relationship between income inequality, Black men

	-2Log Likelihood	**Δ**
Physical health		
Model 1	7774967	
Model 2	7504678	270290
Model 3	7488451	16227
Model 4	7488449	2
Self-rated health		
Model 1	7231406	
Model 2	6921646	309759
Model 3	6830218	91428
Model 4	6830216	2
Mental health		
Model 1	9909280	
Model 2	9621238	288042
Model 3	9530448	90789
Model 4	9530441	7

Model 1=Baseline (null model); Model 2=Individual-level predictors and control variables;
Model 3=Individual-level economic variables; Model 4=County–level predictors and control variables.
Criterion for better model fit is assessed by the smaller-is-better principle.

Table 4.20: Comparison of Multilevel Models predicting the relationship between income inequality, Black women

	-2Log Likelihood	**Δ**
Physical health		
Model 1	11768215	
Model 2	11182918	585298
Model 3	11133814	49104
Model 4	11133812	2
Self-rated health		
Model 1	10709170	
Model 2	10127445	581724
Model 3	9989227	138218
Model 4	9989224	3
Model 5		
Mental health		
Model 1	16801330	
Model 2	16237737	563593
Model 3	16199921	37816
Model 4	16199916	6

Model 1=Baseline (null model); Model 2=Individual-level predictors and control variables;
Model 3=Individual-level economic variables; Model 4=County–level predictors and control variables.
Criterion for better model fit is assessed by the smaller-is-better principle.

As the tables show, the -2LL decreases over each model for all health outcomes, indicating that model 4 better fit the data than the other three models in the overall and stratified analyses.

Summary of results section II

In this section, I presented the results of the three tests I used to assess the adequacy of the overall and stratified models of income inequality and health. In step 1, I confirmed that health varies across geographic context. The necessity of using multi-level modeling as the appropriate statistical method was confirmed in step 2. In Step 3, I showed that the model that included all of the variables used in this analysis better fit the data for all three health outcomes. In the next section, I present the results of the multi-level modeling analysis predicting the relationship between individual-level income and contextual-level income inequality, net of relevant covariates.

Result section III: Multi-level modeling

The next section summarizes the results of the SPSS MIXED multi-level regression using maximum likelihood (ML) estimation to predict the effects of individual- and county-level income inequality on the physical, self-rated, and mental health of individuals 51 and older living in the contiguous US. For each health outcome, Model 1 is the null random model used in the likelihood ratio tests described above. In these models the intercept is allowed to vary and includes only the level of clustering (county) with no predictor variables. In the overall analysis, Model 2 adds the individual-level demographic predictor variables of gender and race and the control variables of education, age, coupled status, and insurance status. In the stratified analysis, gender and race are necessarily dropped starting in Model 2. In both the overall and stratified analyses, Model 3 adds the individual-level predictor of logged income and the control variable of logged wealth. Lastly, Model 4 adds the county-level predictor of income inequality and the control variables of logged median county income and metropolitan status.

Overall Models

Tables 4.20-4.22 show the results of the overall multi-level regression models that predict the relationship between income inequality and health, by outcome. Income was predictive ($p<0.001$) of health for all three outcomes but there was no relationship between the Gini coefficient and health. In addition, all individual-level control variables are also predictive of health, while the only significant contextual-level relationship is between median county income and mental health.

Table 4.21: Multilevel Model Regression Predicting the Effect of Income inequality on Self-Rated Health

	Model 1	Model 2	Model 3	Model 4
Intercept	2.764215	3.858109	5.022425	4.748075
Residual	0.718	0.595	0.583	0.581
Variance (grouping=county)	1.066	0.935	0.908	0.908
ICC	.402	.389	.391	.390
Individual-level variables				
Gender (Women=1)		-0.0453***	-0.046***	-0.046***
Race (Blacks=1)		0.164***	0.077***	0.077***
Education		-0.080***	-0.063***	-0.063***
Age		-0.002***	-0.001***	-0.001***
Coupled Status		-0.138***	0.003***	0.003***
Insurance Status				
None		0.166***	0.052***	0.052***
Medicare		0.362***	0.334***	0.334***
Medicaid		0.610***	0.427***	0.427***
VA		0.071***	0.090***	0.089***
Private		-0.099***	-0.052***	-0.052***
Employer		-0.109***	-0.038***	-0.038***
Individual-level economic variables				
Wealth			-0.026***	-0.026***
Income			-0.123***	-0.123***
County-level				
Median county income				-0.008
Metropolitan				-0.062
Gini Coefficient				0.001
*p<0.05; ***p<0.001				
N=14,126				

Table 4.22: Multilevel Model Regression Predicting the Effect of Income inequality on Physical Health

	Model 1	Model 2	Model 3	Model 4
Intercept	1.807460	.654523	1.256790	3.785369
Residual	0.718	0.603	0.599	0.597
Variance (grouping=county)	1.246	1.077	1.070	1.070
ICC	.402	.359	.359	.358
Individual-level variables				
Gender (Women=1)		0.014***	0.013***	0.013***
Race (Blacks=1)		0.176***	0.130***	0.130***
Education		-0.036***	-0.027***	-0.027***
Age		0.019***	0.020***	0.020***
Coupled Status		0.007***	0.080***	0.080***
Insurance Status				
None		-0.049***	-0.108***	-0.108***
Medicare		0.443***	0.429***	0.429***
Medicaid		0.417***	0.322***	0.322***
VA		0.173***	0.182***	0.182***
Private		-0.061***	-0.036***	-0.036***
Employer		-0.038***	-0.001***	-0.001***
Individual-level economic variables				
Wealth			-0.014***	-0.014***
Income			-0.064***	-0.064***
County-level				
Median county income				-0.183
Metropolitan				0.047
Gini Coefficient				-0.001
*p<0.05; ***p<0.001				
N=14,126				

Table 4.23: Multilevel Model Regression Predicting the effect of Income inequality on Mental Health

	Model 1	Model 2	Model 3	Model 4
Intercept	1.450536	4.470628	5.663379	5.613300
Residual	2.125	1.895	1.854	1.853
Variance (grouping=county)	3.395	3.124	3.067	3.067
ICC	.385	.423	.377	.377
Individual-level variables				
Gender (Women=1)		0.209***	0.214***	0.214***
Race (Blacks=1)		-0.033***	-0.165***	-0.165***
Education		-0.109***	-0.086***	-0.086***
Age		-0.022***	-0.019***	-0.020***
Coupled Status		-0.505***	-0.324***	-0.324***
Insurance Status				
None		0.239***	0.078***	0.078***
Medicare		0.281***	0.250***	0.250***
Medicaid		0.954***	0.678***	0.678***
VA		0.059***	0.080***	0.080***
Private		-0.130***	-0.056***	-0.056***
Employer		-0.209***	-0.112***	-0.112***
Individual-level economic variables				
Wealth			-0.049***	-0.049***
Income			-0.124***	-0.124***
County-level				
Median county income				0.006*
Metropolitan				0.050
Gini Coefficient				0.000
*p<0.05; ***p<0.001				
N=14,126				

Income is protective health for all three outcomes. For each natural logarithm increase in income the mean of self-rated health increases by 0.123 ($p<0.001$) and the mean number of reported diagnosed diseases and depressive symptoms falls by 0.063 ($p<0.001$) and 0.124 ($p<0.001$), respectively. Gender and race are also highly predictive of health. Women over 50 are associated with better self-rated health than similarly aged men (-0.041 $p<0.001$). On the other hand, women are more at risk than men for worse physical (0.013 $p<0.001$) and mental health (0.214 $p<0.001$). Middle- and older-aged Blacks have worse self-rated health (0.077 $p<0.001$) and report more diagnosed diseases than older Whites (0.130 $p<0.001$). Conversely, Blacks have better mental health than Whites, as they report fewer symptoms of depression (-0.165 $p<0.001$). County-level income inequality has no effect on health.

Stratified Models

Tables A.1-A.12 (in Appendix 1) show the results of multi-level modeling predicting the relationship between income inequality and health, by race and gender group. The tables are organized by health outcome and include one table for each of the race and gender groups: White men, White women, Black men, and Black women. Just as with the descriptive results presented above, these results show that health varies by race and gender group. Before delving more deeply into the results of these stratified models, there is one general aspect that should be pointed out. In all 12 models (and the 3 overall models, for that matter), Model 3, which includes the individual-level economic variables of income and wealth, has the greatest impact for all predictor and control variables included in this analysis. In fact, the contextual-level variables in Model 4 have almost no impact on the estimates of effects, as they are

identical in all but a few incidences. A few potential reasons for these lackluster results are detailed in Chapter 5.

Table 4.24: Effect of income on health by race and gender (White men=reference group)

	Total	White women	Black men	Black women
Self-rated health	-.123***	-0.136***	-0.110***	-0.089***
Physical health	-.064***	-0.087***	-0.045***	-0.088***
Mental health	-.124***	-0.198***	-0.175***	-0.112***

*** p<.001 in overall multi-level regression models

Table 4.23 shows the stratified results of income on the three health outcomes. The effect of one unit increase in the natural logarithm of income is protective of health in all cases, but the benefit of the same increase varies by race and gender.

CHAPTER 5: FINDINGS AND DISCUSSION

The purpose of this research is to examine the relationships between individual- and contextual-level income inequality and health for a middle- and older aged representative population in the United States. This study has two main findings. First, this research finds that an increase in income predicts increases in self-rated, physical, and mental health, but that these increases vary profoundly by race and gender. Contrary to expectations that there would be no racial or gender differences in the effect of increased income on health, Women and Black men benefit more than White men from the same increase in natural logarithm income. The second finding of this research is that a contextual level measurement of income inequality has no effect on the physical health of middle and older aged individuals. Recognizing the ways that amounts of income and their distributions are connected to poor health outcomes may provide new insights into identifying the groups that are most vulnerable to these inequalities.

There are both methodological and substantive potential explanations for these findings. First, however, it is necessary to state that the use of causal terms like “effects of race” or “effects of gender” in no way alters this dissertation’s understandings of race and gender as being social constructions that are historically, geographically, and contextually defined (Zuberi and Bonilla-Silva 2008; Brown and Misra 2003; Nakano Glenn 2004; Stoler 2002). Interpretations of health statistics outside of this social construction paradigm often list race and gender as being risk factors for certain diseases or conditions. In other words, ahistorical research construes being Black and/or a woman as a cause for poor health, just like obesity causes heart disease or

smoking causes cancer (Zuberi and Bonilla-Silva 2008). The real question is not how race or gender causes a person to have poor health, but rather how the material conditions that cause poor health are mediated by race and gender[2]. Having written that, though, the statistical methods used to study variation in health outcomes require us to use some type of measurement of race and gender. This research includes only Black and White men and women. In doing so, it loses the ability to understand additional inequalities that are based on other racial or gender identities, as well as the intersections of all race and gender identified differences. Similarly we must recognize the ways that statistical methods privilege some social groups over others. This means that one dominant social group (most commonly White men) is used as a reference to which all other groups are compared. To counter this restricted view of race and gender, I employ McCall's (2005) intercategorical approach to created profiles in the last chapter that describe what inequality looks like separately for each race and gender group.

I have structured the discussion of this study's two main findings hierarchically and will discuss them in separate sections, with the individual-level findings first and the contextual-level finding later in the chapter. Within each section, I organize the discussion by the research questions and hypotheses included earlier in this dissertation.

Individual-level Finding

Research Question 1: Is there a link between individual-level income and poor health? If so, who is the most affected by it? This question is answered by the results detailed in Chapter 4 that tested these two hypotheses:

[2] The use of the term "mediated" here does not imply statistical mediation but the ways that income in the US is stratified by race and gender.

H1: Based on Link and Phelan's structural theory of fundamental cause, there will be a positive association between individual-level income and self-rated, physical, and mental health.

H1a: If H1 is supported, fundamental cause theory would predict that the value of this positive association would benefit individuals in groups that are higher in the social hierarchy (e.g. White men) than those in groups that are lower in the hierarchy.

For income to be a fundamental cause of health it must first be associated with multiple health outcomes (Link and Phelan 1995; Phelan, Link and Tehranifar 2010). Additionally, fundamental cause theory predicts that all individuals with more income will have better health than all with less income, regardless of the race and gender groups to which they belong. This research finds evidence that income is positively associated with overall self-rated, physical, and mental health outcomes, as well as for all four race and gender groups represented in the stratified analysis. Therefore, the first main finding of this dissertation supports H1 and Link and Phelan's theory that income is a fundamental cause of health for middle- and older-aged White and Black men and women in the US.

However, when investigating the effects that individual-level income can have for race and gender groups, this study finds limited support for H1a. Rather than the group that has the highest position in the gender and race systems featured in the US benefitting more from increased income, those with lower positions seem to accrue the most benefit. A potential methodological explanation for this finding of partial support for H1a concerns the shape of the relationship between income and health, while a combination of historical practices that differentiate the lives of Black and White men and women today make up substantive potential explanations.

Individual-level discussion—Methodological explanation

Some scholars contend that the shape of the relationship between income and health is mostly linear (Marmot et al 1984) while others write that it is curvilinear (Wagstaff and Van Doorlear 2000; Mackenbach 2012). In a linear relationship, each unit increase in income results in a concomitant increase in health. In such a relationship, there would be no difference in the amount of benefit each group receives from increased income because all would benefit equally. The curvilinear relationship between income and health, on the other hand, is thought to be mostly linear only up to a certain point. After this point, the degree of increase flattens so that those at the upper end of the distribution receive less benefit to their health for each increase in income than those at the bottom of the distribution.

This perspective is explained by what Scanlon (2006) calls “heuristic rule X”. This rule describes the statistical tendency that when groups differ in health outcomes, the more rare the outcome, the greater the difference will be. For example, this research shows that middle- to older-aged White men have the most income, followed by similarly aged White women, then Black men, and then Black women with the least amount of income. If physical health is dependent on income, as H1 found, than those with the least amounts of income would generally be more susceptible to poor physical health. If we combine these two findings than White women and Blacks would necessarily comprise a larger portion of the segment of the population susceptible to poor health. It only stands to reason, then, that any substantial increase in income would necessarily decrease their percentage of the population in poor health.

Individual discussion—Substantive explanations

In addition to the methodological explanation above, there are also potential substantive structural explanations. Structural explanations of health inequalities are based on the components of general social stratification detailed in the introduction that account for differences in health based on the strata individuals are sorted into and the difference in value of resources for each stratum. Structural theories, like Link and Phelan's theory of fundamental cause predict that individuals sorted into groups with less income will have worse health than those in groups with more income. Since increased income protects the health of all race and gender groups, this research supports that theory. However, there is also cause to question this theory because the value of increased income is different for the health of the three non-reference groups (i.e. White women and Blacks). In this section, I discuss three alternative structural perspectives that may explain these findings.

Substantive explanations—Self-rated health

First, a structural argument may still fit if one believes the individual-level findings in this research are more indicative of the outcomes measured than of any deficit in the overall argument. Thus, those who report excellent self-rated health are not necessarily in better health than those who report poor health. It may be that differences exist in how race groups perceive health (Ferraro et al 1997; Ferraro and Kelley-Moore 2001), or that they may have different reporting patterns (Liang et al 2010). If this were so, than the race system in the US still structures health.

Substantive explanations—Physical health

Second, for physical health, if an individual avoids contact with the health care community, the common diseases that make up the physical health index will not be detected no matter how many symptoms one may display. In this case, it may be this avoidance behavior that is the cause for low numbers of diagnosed diseases and not the actual health of the individual. Systematic racism and gendered social relations in the US are at the root of such avoidance behaviors and may explain the different protective effects that income has on the physical health of those 51 and older.

In the case of systematic racism, there are countless examples of inhumane medical experimentation conducted by the White medical community, with Black men and women as their subjects (Feagin and Bennefield 2014). For example, Black women suffered experimentation with their reproductive systems, and many of the gynecological advances that were made in the later half of the 19th century were the result of brutal experiments with female slaves (Washington 2006). Black men have also been subjects of dehumanizing medical research such as the experiments conducted at Tuskegee Institute, where a promising treatment for syphilis was intentionally withheld in order to examine the neurological effects of the disease. Keeping this historical context in mind, it is not surprising that Black levels of distrust in the US health care system are much higher than White's and as a result, many Blacks avoid interacting with health care professionals regardless of their income (Boulware et al 2003; Washington 2006). Differences in the effects of increased income, then, may not mean that Blacks actually have fewer physical disease, but rather fewer official diagnoses.

Avoidance behavior is also implicated in gendered social relations and the finding that the physical health of women is benefitted by increased income. Women live longer than men even though men have considerably more income (Springer and Mouzon 2011). This structural argument says that men may avoid seeking healthcare because of stereotypical beliefs about masculinity (O'Brien, Hunt, and Hart 2005; Courtney 2003; 2000). Further, men with strong beliefs about masculinity do not benefit from increased income, as their probability of obtaining health care decreases as their income increases (Springer and Mouzon 2011). The effective result of avoidance behavior by men, then, is not that women have fewer diseases than men. It is just that women know about and can report the diseases they have and men cannot because they have less contact with doctors.

Substantive explanations—Mental health

Finally, for mental health, a structural theory would predict that individuals in groups that have traditionally been less advantaged in the US would experience worse mental health than those in advantaged groups. At first glance the results of this research may seem to negate that structural argument as the mental health of White men, the group that has been thought to be the most advantaged in hierarchically based gender and race systems, benefits the least from increased income. An even closer inspection of these findings may further contest a structural explanation since it reveals the extent of this disadvantage, as the same amount of increased income protects the mental health of Black women, Black men, and White women about three to five times more than that of White men.

However, it may also be that men and women form alternative gender and race hierarchies (Rosenfield 2012). In addition to the structural gendered argument above concerning avoidance behavior, alternative conceptions of femininities and masculinities that lead to more externalizing of emotions may be linked to the mental health findings in this research. The split that occurred during the Industrial revolutions between the public and private spheres of life connected dominant ideas about femininity to emotion work that emphasized nurturing and sensitivity, and masculinity to assertiveness and power (Connell 1995). Rosenfield (2012) argues that while Blacks' conceptions of masculinity do overlap with these dominant ideas to some extent, their conceptions of masculinity and femininity differ from Whites' conceptions. Because Black women were never completely in the private sphere, as White women were more likely to be, their definitions of femininity also included paid work and independence. These beliefs about femininity were then used to socialize future generations of Black women to be strong and self-reliant (Collins 1997). These values of an alternative version of femininity help Black women to counteract their lower position in the gender hierarchy. Schnittker and McLeod (2005) write that an individual's perception of their position in a social structure influences their mental health more than their objective position. Thus, an alternative gender and race hierarchy may explain how the same increase in income could have a greater protective effect on the mental health of Black women.

Contextual-level Findings

Research Question 2: Does high income inequality have a negative effect on health? If so, are there gender and race specific impacts? This question is answered by the results detailed in Chapter 4 that tested these two hypotheses:

H2: Based on the ICC, there is a negative association between contextual-level income inequality and health.

The second main finding of this research is that high income inequality has no effect on the health of older and middle aged individuals. When results contrary to our expectations are found, there is always the temptation to drop that part of the analysis and focus more closely on positive results in other parts of the project. I did not do that in this dissertation because negative effects of income inequality is a finding, too, since it places this study in the completely unsupportive, (No significant positive findings) category in Table 2.1 from page 24 in Chapter 2. Another reason I did not remove the contextual portion in this analysis, regardless of its lackluster results, is that any future work in this area would require a multi-level approach in order to fully account for both individual- and contextual-level variables.

One possible reason for this lack of association may be that the mechanisms that have been proposed to link contextual-level income inequality to poor health outcomes may not be relevant for this population. For example, some argue that income inequality causes “under-investment” in social goods that are for the common good of a society (Kawachi and Kennedy 1999). This means that specialized services like public hospitals, public schools, roads, and recreation areas are less likely to be authorized and have public money spent on them. Perhaps such reductions in public goods affect younger populations more than older ones?

A second mechanism that has been used to explain the negative relationship found in other research is the effect of relative deprivation on individual health (Kawachi et al 1997; Kondo et al 2008). This mechanism is also called a “psychosocial theory” since it is the perception of one’s own position in society that may have a direct effect

on a person's health (Wilkinson 2005; Wilkinson and Pickett 2009). In this way of thinking, individual health is harmed by the stress that is caused by comparing the conditions of one's life to others, such as feelings of lack of control over their own lives and anxiety about their place in a social hierarchy relative to others. As was shown earlier in this research, older individuals report less amounts of these types of emotional or depressive symptoms, so they may not have as much anxiety about their position in society as younger people.

Discussion summary

Link and Phelan's theory of fundamental cause and the ICC have both been proposed in the literature to explain the persistent relationship between income inequality and health. The research supports the theory of fundamental cause as a reason for the health differences noted here. On the other hand the ICC was not supported. Lynch et al's (2000) explication of the neo-materialist point of view includes a metaphor that may explain why income matters more than contextual-level differences. The metaphor begins with asking the reader to imagine an airplane, with some people in first class and some people in economy class. After a long flight, when the plane lands the people who flew in first class may physically feel better than those in economy class. After all, since their seats were bigger, their muscles and joints probably are not as stiff as those of the passengers whose seats were cramped closely together in economy class. In addition, first class seats are also more comfortable, so those passengers may even have been able to sleep well and, thus, feel more rested than those in economy class. First class passengers also receive better food and more personal service. An individual-level explanation, then, would say that all of these

advantages of flying first class matter to a person's health because they affect the material being of a person's body and mind.

A contextual-level explanation of the effects that first class and economy class airplane travel would ask the reader to imagine the feelings that economy class passengers have as they walk through the first class sections as they are boarding and deplaning. Using the psychosocial theory, for certain individuals the knowledge that some of their fellow passengers have access to all the advantages mentioned above while they do not, might make people feel worse about their position on the airplane. These bad feelings will, then, lead to poor health for those in economy class. Others have found support for the income inequality hypotheses. Across the board, though, this research shows that the actual material condition of one's life matters to the health of middle-and older individuals.

CHAPTER 6: LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Limitations

As with all social research, there are limitations to this study. In this section I identify eight limitations that may have had an effect on the findings in this research.

Cross-sectional vs longitudinal data

First, this dissertation is limited because it uses cross-sectional instead of longitudinal data. This means that the effects of income and income inequality on the health of those over 50 are examined at one concrete point in time only. Some scholars argue that poor health accumulates over the life course, so research in this area should also analyze earlier life experiences as these antecedents may have a large influence on present-day health (Elo 2009). HRS does have extensive longitudinal data that would allow me to examine how the relationships between income and income inequality change over time. However, change was not the focus of this research. Rather, I wanted to establish how these relationships varied by race and gender group. Now that I have a picture of how income affects various social groups, and that income inequality has no effect, a longitudinal aspect could be to added to a future research agenda.

Second, as highlighted in the conceptual map presented in Chapter 2, the research presented here argues that low income causes poor health. It is also possible, though, for the association to be reversed so that poor health causes low income (Smith 2004). Reverse causation could happen with a “health shock” that could block someone from their full potential to earn income, as well as deplete the resources they may already have. For example, if a respondent had a heart attack at age 50, he/she may

have to take an extensive leave from work to recover. Since this is the point in one's working career that we would expect to be their prime earning time, such a shock could have an immense negative effect on his/her income. Further, if the health shock were massive enough, a respondent's wealth may also be negatively affected. For instance, if a respondent was diagnosed with cancer at age 50, she/he may consider retiring early, meaning that she/he may have to pay steep penalties to access a retirement fund before being fully vested. While some argue that health shocks are "not the primary mechanism between the association between income and health" (Lynch et al 2004:10), this study cannot speak to this possible problem of causality.

A third limitation of this dissertation has to do with temporal issues of using cross-sectional data. Mellor and Milyo (2001) argue that it is possible that any association found in research of this type could be an artifact of the particular time period being examined. As the measures I use to assess income inequality are estimates from 2006, it is possible that some unaccounted for historical event occurred may have intervened on the pathway between income inequality and health (e.g. the beginning of the recession that was fully realized in 2008). In addition to potential historical artifacts, it is also possible there may be a lag effect of a proposed predictor variable that is not accounted for in this analysis (Blalock 1994). This means that the effects of an increase or decrease in income, or the substantial increase in income inequality since the 1970s in the US, may not be temporally observed, but rather experience at a later point in time.

Potential selection bias

The final area that could limit this research is due to the possibility of two types of selection bias. First, since the respondents in the HRS are interviewed in middle- and older-age, it is possible that differing mortality rates may have altered the representativeness of the sample due to left truncation (Liang et al 2010). In the case of this research, the reasoning for potentiality of selection bias is: if income is protective of health and Whites are more likely than Blacks to have high levels of income, then it is likely that a greater proportion of Blacks than Whites in poor health would have died before they became age-eligible for the study. In other words, Blacks who survive into middle- and older-age may just be healthier than similarly aged Whites. This would mean that the racial differences in health found in this research might actually be greater in the general population (Liang et al 2010).

Second, the use of proxy interviews in the HRS may be the source of another potential selection bias (Steffick 2000). Since proxy interviews are allowed only when a respondent has severe physical or cognitive limitations, which are conditions that increase with age, older respondents who do not need a proxy are probably healthier than others in their age group. As this research includes a depression measure that is not included in proxy interviews, the CES-D scale may not be fully representative of the mental health of this age group.

Last, it is possible that the findings of this dissertation are limited because respondent couplehood is not accounted for, since fully two thirds of the sample were either married or in marriage like relationships. Income for respondents who are coupled is the same since they are members of the same household. As such, since income is

so strongly related to health, couples are more likely to have similar health statuses than not. This is important for two reasons. First, this homogeneity in health would affect the intra-class correlation (ICC) since it is a ratio of the within county variance to the between county variance. In other words, what may look like lack of variation in health at the county level is actually lack of variation at the individual level. If this sample problem dramatically changed the ICC, the choice of methods could be affected. More importantly, though, this lack of variability could be responsible for the absence of an effect of income inequality on health. I account for this limitation, and others, in the next section.

Avenues for extension of this research

This research adds to the empirical literature that examines the effects of income inequality on health. However, there are many questions left unasked that may have implications for future research, both in my personal research agenda as well as for the scientific community in general. In this section I identify four potential avenues of personal extension.

First, and by far the most important to me personally, would be a potential re-examination of this research with full geographic identifiers, instead of masked ones. While I was extremely fortunate to be granted this unique access to the restricted HRS data, I think other characteristics of each county may add more predictive ability to this research in the future. Previous research indicates that neighborhood characteristics and composition are also linked to health (Ross 2000; Ross and Mirowsky 2001). Some of these characteristics are the spatial segregation of income (Massey and Denton 1988; Reardon and Bischoff 2011) and residential segregation in general (Williams and

Collins 2001). With access to full geographic data, I would be able to link the counties represented in this research to other sources of data that include these types of neighborhood characteristics.

Second, associations between control variables and income inequality were uncovered but left unanalyzed in this research. These relationships would be a good springboard for my future research agenda. For example, although previous research has shown that being married is generally protective of health (Lillard and Waite 1995; Mirowsky and Ross 2003), during retirement it may be particularly beneficial (Pienta, Hayward, and Jenkins 2000; Hughes and Waite 2009). Others write that the *nature* of the marriage relationship is more important than the mere *presence* of a spouse or long time cohabitating companion (Bookwala and Jacobs 2004). This dissertation finds evidence of the beneficial effects couplehood has on health, but also finds that they vary substantially by race, gender and outcome.

A third area of potential extension of this research could be to more closely investigate the findings about insurance status. For example, this research finds evidence that having no insurance is protective of the physical health of Blacks and White men but not White women. While caution should be used in interpreting the effects of insurance status on health, as they do not always represent discrete and/or exhaustive groups, still it would be interesting to examine these implications in light of avoidance behavior being a potential explanation for individual-level differences in health. Further, the age group represented by the HRS is essential to insurance status, as the variation in type of respondent insurance is eliminated the moment they turn 65

and they age into Medicare. Any future work in this area needs to be cognizant of this age component.

Finally, future extensions of this work could include the public vs. private nature of the source of the insurance. In general, this dissertation finds that public sources of insurance (e.g., Medicare, Medicaid, VA) have a negative effect on health and that private or employer provided insurance are protective of health. But these relationships also vary by health outcome and race and gender group. What is it about the nature of Medicaid that is a risk to the self-rated and mental health of poor White men 51 and older? Or the nature of Medicare that is a risk to the physical health of similarly aged Black women? Is it merely the presence of insurance that matters the most, or does the quality of healthcare available to differently income-resourced individuals matter more?

Contributions for future research

The main contribution of this research is emphasizing the need to recognize that social research is naturally organized at more than one level of aggregation. Consequently, the methods used to study it must also capture multiple levels. One of the main critiques of research in this literature is that the use of correlational and/or single-level linear methods confounds the effect of income with contextual-level inequality, leading to an ecological fallacy (Backlund, Sorlie and Johnson 1999; Subramanian and Kawachi 2004; Lynch 2004). In the past, it may have been true that there was limited access to the individual- and contextual-level data needed to be able to study this problem on both levels, but this should not be the case today for established researchers. Future work in this area should reflexively use multi-level

methods in order to understand the simultaneous contributions of individual- and contextual-income inequality.

APPENDIX: A

Table Appendix.1: Multilevel Regression Predicting the Effect of Income Inequality on SRH Health, White men

	Model 1	Model 2	Model 3	Model 4
Intercept	2.691	3.678	4.616	5.963
Residual	.844	.759	.737	.736
Variance (grouping=county)	.953	.846	.827	.827
ICC	0.470	0.473	0.471	0.471
Individual-level variables				
Education		-0.088***	-0.073***	-0.073***
Age		0.002***	0.004***	0.004***
Coupled Status		-0.111***	-0.010***	-0.010***
Insurance Status				
None		0.179***	0.048***	0.048***
Medicare		0.296***	0.270***	0.000***
Medicaid		0.693***	0.536***	0.002***
VA		0.099***	0.101***	0.001***
Private		-0.193***	-0.146***	0.000***
Employer		-0.120***	-0.059***	0.000***
Individual-level economic variables				
Wealth			-0.026***	-0.026***
Income			-0.096***	-0.096***
County-level				
Median county income				-0.106
Metropolitan				-0.014
Gini Coefficient				-0.000
***p<0.001				
N=14,126				

Table Appendix.2: Multilevel Regression Predicting the Effect of Income Inequality on SRH Health, White women

	Model 1	Model 2	Model 3	Model 4
Intercept	2.699	3.893	5.218	4.701
Residual	.812	.703	.688	.685
Variance (grouping=county)	1.010	.889	.864	.864
ICC	0.446	0.442	0.443	0.442
Individual-level variables				
Education		-0.083***	-0.064***	-0.064***
Age		-0.003***	-0.003***	-0.003***
Coupled Status		-0.170***	-0.014***	-0.014***
Insurance Status				
None		0.210***	0.098***	0.098***
Medicare		0.385***	0.356***	0.356***
Medicaid		0.680***	0.466***	0.466***
VA		0.068***	0.106***	0.106***
Private		-0.064***	-0.017***	-0.017***
Employer		-0.086***	-0.018***	-0.018***
Individual-level economic variables				
Wealth			-0.028***	-0.028***
Income			-0.136***	-0.136***
County-level				
Median county income				0.021
Metropolitan				-0.111
Gini Coefficient				0.000
***p<0.001				
N=14,126				

Table Appendix.3: Multilevel Regression Predicting the Effect of Income Inequality on SRH Health, Black men

	Model 1	Model 2	Model 3	Model 4
Intercept	3.053	4.954	5.454	9.668
Residual	.715	.654	.644	.634
Variance (grouping=county)	.916	.814	.786	.786
ICC	0.438	0.446	0.450	0.447
Individual-level variables				
Education		-0.053***	-0.036***	-0.036***
Age		-0.022***	-0.014***	-0.014***
Coupled Status		-0.060***	0.106***	0.106***
Insurance Status				
None		-0.168***	-0.140***	-0.140***
Medicare		0.516***	0.461***	0.461***
Medicaid		0.300***	0.175***	0.175***
VA		0.184***	0.172***	0.172***
Private		-0.007**	0.084***	0.084***
Employer		-0.242***	-0.134***	-0.134***
Individual-level economic variables				
Wealth			-0.022***	-0.022***
Income			-0.110***	-0.110***
County-level				
Median county income				-0.293
Metropolitan				0.143
Gini Coefficient				-0.003
***p<0.001				
N=14,126				

Table Appendix.4: Multilevel Regression Predicting the Effect of Income Inequality on SRH Health, Black women

	Model 1	Model 2	Model 3	Model 4
Intercept	3.200	4.387	4.980	5.472
Residual	.655	.513	.519	.510
Variance (grouping=county)	.882	.761	.735	.735
ICC	0.426	0.403	0.414	0.410
Individual-level variables				
Education		-0.064***	-0.044***	-0.044***
Age		-0.010***	-0.008***	-0.008***
Coupled Status		-0.117***	0.021***	
Insurance Status				
None		0.043***	-0.001	-0.001
Medicare		0.335***	0.369***	0.369***
Medicaid		0.515***	0.417***	0.417***
VA		-0.077***	-0.049***	-0.049***
Private		0.246***	0.285***	0.285***
Employer		-0.071***	0.014***	0.014***
Individual-level economic variables				
Wealth			-0.023***	-0.023***
Income			-0.089***	-0.089***
County-level				
Median county income				-0.136
Metropolitan				0.112
Gini Coefficient				0.002
***p<0.001				
N=14,126				

Table Appendix.5: Multilevel Regression Predicting the Effect of Income Inequality on Physical Health, White men

	Model 1	Model 2	Model 3	Model 4
Intercept	1.753	.262	.569	5.602
Residual	.911	.805	.793	.780
Variance (grouping=county)	1.183	1.010	1.006	1.006
ICC	0.435	0.443	0.441	0.437
Individual-level variables				
Age		0.024***	0.025***	0.025***
Education		-0.034***	-0.027***	-0.027***
Coupled Status		0.090***	0.131***	0.131***
Insurance Status				
None		-0.197***	-0.257***	-0.257***
Medicare		0.435***	0.425***	0.425***
Medicaid		0.172***	0.102***	0.102***
VA		0.219***	0.220***	0.220***
Private		-0.115***	-0.092***	-0.092***
Employer		-0.071***	-0.043***	-0.043***
Individual-level economic variables				
Wealth			-0.014***	-0.014***
Income			-0.031***	-0.031***
County-level				
Median county income				-0.342*
Metropolitan				0.106
Gini Coefficient				-0.003**
***p<0.001				
N=14,126				

Table Appendix.6: Multilevel Regression Predicting the Effect of Income Inequality on Physical Health, White women

	Model 1	Model 2	Model 3	Model 4
Intercept	1.759289	.951573	1.783896	1.772018
Residual	.804467	.701058	.703735	.702709
Variance (grouping=county)	1.118445	.961552	.953770	.953770
ICC	0.418	0.422	0.425	0.424
Individual-level variables				
Age		0.0180***	0.0181***	0.0181***
Education		-0.0502***	-0.0391***	-0.0391***
Coupled Status		-0.0634***	0.0263***	0.0263***
Insurance Status				
None		0.0740***	0.0166***	0.0166***
Medicare		0.4243***	0.4072***	0.4072***
Medicaid		0.4389***	0.3271***	0.3271***
VA		0.0678***	0.0899***	0.0899***
Private		-0.0021**	0.0223***	0.0223***
Employer		0.0179***	0.0561***	0.0561***
Individual-level economic variables				
Wealth			-0.0119***	-0.0119***
Income			-0.0872***	-0.0872***
County-level				
Median county income				0.005
Metropolitan				-0.068
Gini Coefficient				-9.460E-7
***p<0.001				
N=14,126				

Table Appendix.7: Multilevel Model Regression Predicting the Effect of Income inequality and Physical Health, Black men

	Model 1	Model 2	Model 3	Model 4
Intercept	1.873322	.948556	1.136566	4.851565
Residual	1.070714	.967526	.948234	.936335
Variance (grouping=county)	1.126194	1.016167	1.009916	1.009916
ICC	0.487	0.488	0.484	0.481
Individual-level variables				
Age		0.0133***	0.0170***	0.0170***
Education		-0.0217***	-0.0143***	-0.0143***
Coupled Status		0.1046***	0.1811***	0.1811***
Insurance Status				
None		-0.3350***	-0.3177***	-0.3177***
Medicare		0.3818***	0.3583***	0.3583***
Medicaid		0.3070***	0.2423***	0.2423***
VA		0.3924***	0.3827***	0.3827***
Private		-0.2699***	-0.2265***	-0.2265***
Employer		0.0410***	0.0907***	0.0907***
Individual-level economic variables				
Wealth			-0.0121***	-0.0121***
Income			-0.0454***	-0.0454***
County-level				
Median county income				-0.3109
Metropolitan				0.3456
Gini Coefficient				-0.0014
***p<0.001				
N=14,126				

Table Appendix.8: Multilevel Regression Predicting the Effect of Income Inequality on Physical Health, Black women

	Model 1	Model 2	Model 3	Model 4
Intercept	2.101589	2.279301	2.955653	4.499295
Residual	.806479	.659403	.656443	.649389
Variance (grouping=county)	1.153072	.994201	.981912	.981912
ICC	0.412	0.399	0.401	0.398
Individual-level variables				
Age		-0.0004***	0.0005***	0.0005***
Education		-0.0324***	-0.0200***	-0.0200***
Coupled Status		-0.1166***	-0.0199***	-0.0199***
Insurance Status				
None		-0.0311***	-0.0799***	-0.0799***
Medicare		0.5102***	0.5207***	0.5207***
Medicaid		0.4702***	0.4087***	0.4087***
VA		0.0826***	0.1027***	0.1027***
Private		-0.1224***	-0.1062***	-0.1062***
Employer		-0.1814***	-0.1294***	-0.1294***
Individual-level economic variables				
Wealth			-0.0086***	-0.0086***
Income			-0.0877***	-0.0877***
County-level				
Median county income				-0.1903
Metropolitan				0.2334
Gini Coefficient				0.0007
***p<0.001				
N=14,126				

Table Appendix.9: Multilevel Regression Predicting the Effect of Income Inequality on CESD, White men

	Model 1	Model 2	Model 3	Model 4
Intercept	1.084693	3.953425	4.392857	-2.102030
Residual	1.727644	1.634916	1.591877	1.575204
Variance (grouping=county)	2.649343	2.462707	2.423756	2.423756
ICC	0.395	0.399	0.396	0.394
Individual-level variables				
Education		-0.1008***	-0.0845***	-0.0845***
Age		-0.0155***	-0.0115***	-0.0115***
Coupled Status		-0.5651***	-0.4666***	-0.4666***
Insurance Status				
None		0.1080***	-0.0579***	-0.0579***
Medicare		0.1678***	0.1435***	0.1435***
Medicaid		1.4067***	1.2105***	1.2105***
VA		0.0235***	0.0257***	0.0257***
Private		-0.1831***	-0.1112***	-0.1112***
Employer		-0.2169***	-0.1437***	-0.1437***
Individual-level economic variables				
Wealth			-0.0509***	-0.0509***
Income			-0.0421***	-0.0421***
County-level				
Median county income				0.4889*
Metropolitan				-0.0232***
Gini Coefficient				0.0028
***p<0.001				
N=14,126				

Table Appendix.10: Multilevel Regression Predicting the Effect of Income Inequality on CESD, White women

	Model 1	Model 2	Model 3	Model 4
Intercept	1.544707	4.769081	6.718119	11.092397
Residual	2.691152	2.463541	2.398280	2.391413
Variance (grouping=county)	3.420340	3.221509	3.156414	3.156414
ICC	0.440	0.433	0.432	0.431
Individual-level variables				
Education		-0.1114***	-0.0800***	-0.0800***
Age		-0.0237***	-0.0223***	-0.0223***
Coupled Status		-0.4970***	-0.2546***	-0.2546***
Insurance Status				
None		0.2959***	0.1123***	0.1123***
Medicare		0.3616***	0.3178***	0.3178***
Medicaid		0.8087***	0.4588***	0.4588***
VA		0.0062	0.0639***	0.0639***
Private		-0.1298***	-0.0536***	-0.0536***
Employer		-0.1760***	-0.0694***	-0.0694***
Individual-level economic variables				
Wealth			-0.0491***	-0.0491***
Income			-0.1983***	-0.1983***
County-level				
Median county income				-0.3954
Metropolitan				0.1062
Gini Coefficient				-0.0004
***p<0.001				
N=14,126				

Table Appendix.11: Multilevel Regression Predicting the Effect of Income Inequality on CESD, Black men

	Model 1	Model 2	Model 3	Model 4
Intercept	1.667743	4.855706	5.625449	17.760446
Residual	2.271627	1.919556	1.824591	1.739914
Variance (grouping=county)	2.536131	2.272965	2.195817	2.195817
ICC	0.472	0.458	0.454	0.442
Individual-level variables				
Education		-0.1203***	-0.0933***	-0.0933***
Age		-0.0331***	-0.0201***	-0.0201***
Coupled Status		-0.2366***	0.0375***	0.0375***
Insurance Status				
None		0.5019***	0.5535***	0.5534***
Medicare		0.4265***	0.3379***	0.3378***
Medicaid		1.0344***	0.8183***	0.8183***
VA		0.8201***	0.7947***	0.7947***
Private		0.3122***	0.4635***	0.4635***
Employer		0.1421***	0.3212***	0.3212***
Individual-level economic variables				
Wealth			-0.0394***	-0.0394***
Income			-0.1745***	-0.1745***
County-level				
Median county income				-0.9787*
Metropolitan				0.8351
Gini Coefficient				-0.0050
***p<0.001				
N=14,126				

Table Appendix.12: Multilevel Regression Models Predicting the Effect of Income inequality on CESD, Black women

	Model 1	Model 2	Model 3	Model 4
Intercept	2.004706	6.962132	7.738332	8.714854
Residual	3.007115	2.824361	2.812225	2.731177
Variance (grouping=county)	4.125778	3.576910	3.542812	3.542812
ICC	0.422	0.441	0.443	0.435
Individual-level variables				
Education		-0.1460***	-0.1239***	-0.1239***
Age		-0.0488***	-0.0466***	-0.0466***
Coupled Status		-0.4671***	-0.3071***	-0.3071***
Insurance Status				
None		0.2702***	0.2125***	0.2125***
Medicare		0.4481***	0.4827***	0.4827***
Medicaid		0.6645***	0.5535***	0.5535***
VA		-0.5594***	-0.5272***	-0.5272***
Private		0.1266***	0.1680***	0.1680***
Employer		-0.5194***	-0.4235***	-0.4235***
Individual-level economic variables				
Wealth			-0.0239***	-0.0239***
Income			-0.1115***	-0.1115***
County-level				
Median county income				0.1221
Metropolitan				0.3643
Gini Coefficient				-0.0057
***p<0.001				
N=14,126				

APPENDIX: B

Table Appendix B.1: Weighted descriptive statistics, overall and stratified by Gini coefficient, White men

	White Men		Low inequality		Medium inequality		High inequality	
	N=5101		N=1875		N=1713		N=1513	
	Mean/		Mean/		Mean/		Mean/	
	Percent	SD	Percent	SD	Percent	SD	Percent	SD
Dependent Variables								
Self-rated health (1-5)	2.64	1.09	2.63	1.065	2.64	1.074	2.66	1.140
Physical health (0-5)	1.59	1.21	1.59	1.203	1.62	1.213	1.55	1.208
Mental health (0-8)	1.16	1.77	1.13	1.728	1.06	1.659	1.31	1.916
Independent Variables								
Individual-level								
Education	13.56	2.73	13.43	2.69	13.530	2.60	13.79	2.91
Age	65.02	9.83	64.03	9.696	65.93	9.991	65.32	9.718
Coupled Status	79.02%	—	80.6%	—	78.8%	—	77.2%	—
Medicaid	1.88%	—	1.2%	—	2.4%	—	2.2%	—
Medicare	46.56%	—	41.6%	—	51.6%	—	47.5%	—
VA	06.73%	—	6.9%	—	6.0%	—	7.4%	—
Private	14.78%	—	16.5%	—	14.0%	—	13.4%	—
Employer	59.03%	—	62.0%	—	57.1%	—	57.2%	—
No Insurance	05.3%	—	5.0%	—	4.5%	—	6.7%	—
Income*	10.88	1.19	10.86	1.23	10.88	1.11	10.91	1.21
Wealth*	11.57	4.45	11.49	4.42	11.70	4.25	11.55	4.72
County-level								
Metropolitan status			63.3%	—	82.2	—	84.4	—
Med co. income			$56238	$14569	$52352	$13575	$48782	$12627

Table Appendix B.2: Weighted descriptive statistics, overall and stratified by Gini coefficient, White women

	White women		Low inequality		Medium inequality		High inequality	
	N=6853		N=2454		N=2338		N=2061	
	Mean/		Mean/		Mean/		Mean/	
	Percent	SD	Percent	SD	Percent	SD	Percent	SD
Dependent Variables								
Self-rated health (1-5)	2.68	1.10	2.67	1.084	2.68	1.102	2.68	1.12
Physical health (0-5)	1.65	1.16	1.65	1.174	1.68	1.133	1.62	1.15
Mental health (0-8)	1.53	2.01	1.49	1.981	1.53	2.009	1.59	2.04
Independent Variables								
Individual-level								
Education	13.12	2.39	13.01	2.27	13.12	2.38	13.25	2.54
Age	66.3	10.46	65.63	10.46	67.18	10.34	66.16	10.51
Coupled Status	59.5%	—	62.9	—	58.6%	—	56.3%	—
Medicaid	04.3%	—	3.9%	—	4.7%	—	4.5%	—
Medicare	51.3%	—	48.3	—	54.5%	—	51.6%	—
VA	4.0%	—	4.3%	—	3.7%	—	4.0%	—
Private	17.7%	—	19.7%	—	17.6%	—	15.3%	—
Employer	55.7%	—	57.2%	—	54.1%	—	55.4%	—
No Insurance	4.6%	—	4.3%	—	4.7%	—	4.8%	—
Income*	10.59	10.59	10.59	1.17	10.58	1.14	10.60	1.12
Wealth*	11.38	11.38	11.29	4.38	11.50	4.00	11.35	4.45
County-level								
Metropolitan status			62.1	—	81.1	—	84.7	—
Med co. income			$55877	$14291	$52358	$13587	$48681	$12307

Table Appendix B.3: Weighted descriptive statistics, overall and stratified by Gini coefficient, Black men

	Black men		Low inequality		Medium inequality		High inequality	
	N=767		N=91		N=207		N=469	
	Mean/		Mean/		Mean/		Mean/	
	Percent	SD	Percent	SD	Percent	SD	Percent	SD
Dependent Variables								
Self-rated health (1-5)	3.04	1.14	3.05	1.129	2.92	1.150	3.07	1.15
Physical health (0-5)	1.67	1.25	2.02	1.325	1.81	1.300	1.64	1.22
Mental health (0-8)	1.73	1.90	2.08	2.340	1.66	2.088	1.72	1.83
Independent Variables								
Individual-level								
Education	11.81	3.43	12.48	2.86	11.47	3.77	11.8	3.38
Age	62.54	8.78	61.56	8.42	64.47	9.718	62.00	8.359
Coupled Status	62.65%	—	63.1%	—	67.5%	—	60.7%	—
Medicaid	12.81%	—	8.5%	—	9.0%	—	15.1%	—
Medicare	41.08%	—	43.6%	—	49.6%	—	37.3%	—
VA	09.23%	—	11.8%	—	7.1%	—	9.5%	—
Private	05.66%	—	6.9%	—	6.4%	—	5.1%	—
Employer	46.16%	—	56.7%	—	44.1%	—	44.9%	—
No Insurance	1.19%	—	7.2%	—	11.4%	—	12.9%	—
Income*	10.20	1.48	10.57	.998	10.40	1.14	10.04	1.64
Wealth*	8.36	6.34	10.20	4.701	8.42	6.62	7.97	6.45
County-level								
Metropolitan status			91.7	—	89.2	—	81.0	—
Med co. income			$58554	$15511	$52585	$13370	$44487	$9900

Table Appendix B.4: Weighted descriptive statistics, overall and stratified by Gini coefficient, Black women

	Black women		Low inequality		Medium inequality		High inequality	
	N=1405		N=148		N=343		N=914	
	Mean/	Mean/	Mean/		Mean/		Mean/	
	Percent	Percent	Percent	SD	Percent	SD	Percent	SD
Dependent Variables								
Self-rated health (1-5)	3.21	1.05	3.16	1.117	3.34	1.054	3.19	1.03
Physical health (0-5)	2.02	1.18	2.15	1.247	2.07	1.198	2.00	1.14
Mental health (0-8)	2.08	2.25	2.05	2.284	2.21	2.216	2.03	2.25
Independent Variables								
Individual-level								
Education	12.07	2.99	12.31	2.86	11.93	3.136	12.08	2.96
Age	63.95	9.71	63.40	9.69	66.10	10.367	63.27	9.348
Coupled Status	33.2%	—	32.0%	—	36.1%	—	32.3%	—
Medicaid	18.2%	—	14.0%	—	18.6%	—	18.8%	—
Medicare	46.1%	—	43.6%	—	54.1%	—	43.6%	—
VA	2.7%	—	5.2%	—	1.8%	—	2.6%	—
Private	6.6%	—	1.9%	—	9.9%	—	6.2%	—
Employer	44.1%	—	46.6%	—	41.8%	—	44.5%	—
No Insurance	11%	—	12.0%	—	7.0%	—	12.2%	—
Income*	9.861	1.48	9.61	2.47	9.90	1.29	9.88	1.31
Wealth*	7.57	6.64	8.03	6.41	7.41	6.76	7.54	6.63
County-level								
Metropolitan status			87.6	—	86.3	—	82.0	—
Med co. income			$58125	$17013	$50321	$12369	$44686	$9703

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ABSTRACT

THE EFFECTS OF INDIVIDUAL-LEVEL INCOME AND CONTEXTUAL-LEVELINCOME INEQUALITY ON HEALTH

by

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Advisor: Dr. Krista Brumley

Major: Sociology

Degree: Doctor of Philosophy

The relationship between income inequality and health is often studied at either the individual-level or contextual-level. The purpose of this research is to assess both of these levels, by simultaneously examining the individual and contextual contributions of income inequality on health. To address this research objective, I use data for 14,126 respondents from the 2006 wave of the Health and Retirement Study (HRS), a nationally representative sample of Americans over 50. For this analysis, I use multi-level modeling with fixed and random intercepts to assess the relationship between income inequality and three measures of health. This study has two main findings. First, an increase in individual income predicts better self-rated, physical, and mental health in middle and older aged adults, but that this protective effect varies profoundly by race and gender. The second main finding of this research is that contextual-level income inequality has no effect on the health of those over 50 in the US. The main contribution of this research is that it emphasizes the need for using multi-level modeling when studying this problem in order to more fully understand the simultaneous contribution of individual- and contextual-level income inequality.

AUTOBIOGRAPHICAL STATEMENT

Beth Simmert was born in New Castle, Indiana before moving with her family to Manistee, MI, Cadillac, MI, La Porte, IN, Michigan City, IN, Peoria, IL, Madison, WI, Benton Harbor, MI, Stevensville, MI, Moline, IL, and Austin, MN, where she graduated from High School. During her family's time in Madison (1976-1978), she was one of the first girls in the state of Wisconsin to play Little League Baseball. After high school, she graduated from Moorhead State University with a degree in Secondary Education/History. As a young adult, she worked as a substitute teacher, and then as the shipping and receiving director at a video company in Northeast Missouri. After a number of years out of the labor force, she returned to work in as a home visitor for *Early Head Start* and *Even Start* programs in Flint, MI, where she and her family were living at that time. Beth returned to school and received her Master of Arts in Social Science from The University of Michigan-Flint in August 2009. That fall, she started work on her doctoral degree at Wayne State University, in Detroit, MI. In 2012, Beth secured an internship with the Health and Retirement Study at The Institute for Social Research (ISR) of The University of Michigan in Ann Arbor, MI, where she also worked in the summer of 2013. In February of 2014, Beth accepted a permanent position as a research associate on the Data Production team with The Panel Study of Income Dynamics at the ISR.